Department of Economics

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A Life-Cycle Hypothesis

by Andy Chung and Junsen Zhang

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Department of Economics
University of Reading
Whiteknights
Reading
RG6 6AA
United Kingdom

www.reading.ac.uk

Sleeping Investment: A Life-Cycle Hypothesis

Andy Chung and Junsen Zhang*

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Abstract

This paper develops and tests a life-cycle hypothesis of sleep investment. Motivated by evidence from psychology, aging, and sleep research that the consequences of insufficient sleep become increasingly severe with age, we argue that individuals facing stronger productivity incentives should increasingly preserve sleep as they age. We formalize this idea in a simple life-cycle framework in which sleep is a productive activity that competes with work and leisure for time. We test the framework using longitudinal data from the National Longitudinal Study of Adolescent to Adult Health (Add Health). We focus on adolescent physical attractiveness and college education as two characteristics associated with occupational sorting and long-run productivity incentives. While both characteristics exhibit little association with sleep duration in early adulthood, their relationships with sleep become increasingly positive over the life cycle. Attractive individuals and college graduates experience substantially less negative declines in sleep duration with age and increasingly sleep longer relative to their counterparts in later adulthood. Additional analyses show that these patterns are strongest among workers and are not readily explained by mental health, sleep difficulties, social participation, or reverse causality through sleep affecting later attractiveness. More broadly, the findings suggest that differences in long-run productivity incentives contribute to divergent sleep trajectories over adulthood and support a life-cycle perspective on sleep investment.

JEL classification: I12, J22, J24

Keywords: sleep, life cycle, health investment, physical attractiveness, college education

*Chung: University of Reading, email: chunkit.chung@reading.ac.uk. Zhang: Zhejiang University and Chinese University of Hong Kong, email: jszhang@cuhk.edu.hk. We thank colleagues and seminar participants for helpful comments and suggestions. All remaining errors are our own.

1 Introduction

Sleep is a fundamental input into human health, cognitive functioning, and productivity. As populations age and careers extend later into adulthood, understanding how individuals maintain cognitive capacity, health, and work performance over the life cycle has become increasingly important. A growing body of evidence shows that sleep plays a central role in human capital accumulation and economic performance, affecting cognition, mental well-being, labor productivity, earnings, and healthy aging. Following the path-breaking work of Biddle and Hamermesh (1990), which documented the relationship between wages and sleep, economists have recently shown that insufficient sleep adversely affects earnings, health outcomes, and even aggregate economic performance (Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019; Nguyen et al., 2024). Recent experimental evidence further demonstrates that interventions designed to improve sleep can enhance academic achievement and labor productivity (Giuntella et al., forthcoming). At the same time, research in psychology and aging suggests that the consequences of insufficient sleep, particularly for executive functioning, working memory, episodic memory, attention, vigilance, and cognitive performance, become increasingly severe with age (Cohen et al., 2024; Kim et al., 2013; Miller et al., 2014; Regestein et al., 2004; Sternberg et al., 2013; Kronholm et al., 2009; Krieg et al., 2001). Taken together, these findings suggest that sleep increasingly functions as an investment in maintaining productivity, cognitive capacity, and health over the life cycle.

Despite the growing literature on the economics of sleep, relatively little is known about why sleep investment trajectories diverge systematically across individuals over adulthood. Existing studies primarily examine the average effects of sleep duration (Gibson and Shrader, 2018; Costa-Font et al., 2024), sleep variability and volatility (Hamermesh and Pfann, 2022), or sleep interventions (Giuntella et al., forthcoming), while paying less attention to how incentives to preserve sleep evolve heterogeneously over the life cycle. If sleep increasingly functions as a productivity-preserving investment later in life, then differences in incentives or resources to maintain sleep may contribute to widening inequalities in cognitive functioning, health, and labor-market outcomes over adulthood. This paper investigates whether individuals facing stronger long-run productivity incentives increasingly preserve sleep as they age. Although this hypothesis could apply to many dimensions of heterogeneity, we focus on two particularly important characteristics: physical attractiveness and college education. Both traits predict occupational sorting, earnings trajectories, and entry into occupations where cognitive performance, social interaction, and sustained productivity may become increasingly valuable over the life course.

A well-established literature shows that more attractive individuals earn higher wages, receive more favorable evaluations in educational settings, experience better social outcomes, and enjoy broader labor market opportunities (Hamermesh and Biddle, 1994; Hamermesh and Parker, 2005; Deryugina and Shurchkov, 2015; Scholz and Sicinski, 2015; Stinebrickner et al., 2019). They are also less likely to engage in video gaming (Chung et al., 2025), risky behaviors (Chung and Zhang, 2025; Green et al., 2023), and criminal activity (Mocan and Tekin, 2010), while being more likely to form marital unions (Chung and Zhang, forthcoming). Despite this evidence, little is known about whether physical attractiveness shapes health investments later in life, including the demand for sleep. College education provides a second, more conventional source of productivity-related heterogeneity (see, e.g., Becker, 1993; Card, 1999; Autor and Dorn, 2013), allowing us to examine whether similar life-cycle mechanisms also arise from differences in human capital.

Using longitudinal data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), we document a striking life-cycle pattern: individuals with higher attractiveness sleep increasingly longer relative to others as they age. While attractiveness has only a modest association with sleep during early adulthood, more attractive individuals sleep significantly longer by early midlife. Importantly, we find a parallel pattern for college education: the association between having a college degree and sleep duration also becomes increasingly positive with age. Similarly, the age-related decline in sleep duration is substantially less negative among attractive individuals and college graduates. These findings support the broader interpretation that individuals with stronger long-run productivity incentives increasingly preserve sleep as they age.

We argue that these patterns arise because the productivity return to sleep increases with age. Evidence from psychology and aging research suggests that insufficient sleep has more severe consequences for executive functioning, vigilance, and crystallized cognition during middle and later adulthood than during young adulthood (Scullin and Bliwise, 2015). For example, Cohen et al. (2024) show that poor sleep quality is more strongly associated with deficits in executive functioning and crystallized cognition among older adults. Related longitudinal evidence further indicates that aging amplifies the cognitive and performance costs of sleep problems: middle-aged adults experiencing insomnia report greater daytime impairment, while older adults exhibit larger declines in objective psychomotor vigilance performance

(Kim et al., 2013). Evidence from the English Longitudinal Study of Ageing similarly shows that both sleep quantity and sleep quality are strongly associated with cognitive functioning in later life, particularly for measures of memory and non-amnestic cognition (Miller et al., 2014). Consistent with these findings, Sternberg et al. (2013) document in a large-scale cognitive-performance dataset that sleep duration is strongly associated with performance on tasks involving working memory, attention, and arithmetic reasoning, while cognitive abilities related to fluid intelligence decline more rapidly with age than crystallized abilities. Together, these findings suggest that sleep becomes increasingly important for maintaining productivity-relevant cognitive capacities as individuals age.

This psychological and medical evidence aligns closely with recent economic evidence on the labor-market returns to sleep. Using longitudinal data from Germany and exogenous variation in sleep generated by sunset times, Costa-Font et al. (2024) show that longer sleep causally increases employment, hourly productivity, and earnings, primarily through improvements in mental well-being and work efficiency rather than longer working hours. Their estimates also reveal substantial heterogeneity across age groups: the productivity and earnings effects of sleep are considerably larger among older workers than younger workers. More broadly, recent work on sleep variability and volatility similarly suggests that individuals facing stronger productivity incentives actively stabilize sleep patterns (Hamermesh and Pfann, 2022). Taken together, these findings are consistent with the broader interpretation that sleep plays a progressively more important role in preserving productivity and cognitive functioning later in the life cycle.

Our conceptual framework formalizes this intuition. Individuals allocate time between work, leisure and sleep. Sleep raises productivity but carries an opportunity cost in terms of foregone working or leisure time. The productivity return to sleep increases with age, particularly in occupations where cognitive performance and sustained productivity remain valuable later in life. Physical attractiveness and college education both increase the probability of entering such occupations. The framework therefore predicts that the marginal effects of attractiveness and college education on sleep duration become more positive with age. Equivalently, although sleep duration may decline on average over the life cycle because biological sleep needs and sleep architecture change with age (Ohayon et al., 2004; Li et al., 2018), the decline should be less negative among attractive individuals and college graduates because they face stronger incentives to preserve productivity and cognitive functioning later in life.

Beyond productivity and health, sleep may also influence physical appearance, suggesting a potential bidirectional relationship between sleep and attractiveness itself. We therefore also examine the reverse direction by estimating whether lagged sleep predicts subsequent interviewer-rated attractiveness. This analysis allows us to assess whether the observed life-cycle patterns primarily reflect attractiveness shaping sleep investment, rather than sleep mechanically improving later attractiveness.

This paper contributes to several strands of literature. First, it contributes to the economics of sleep by developing a life-cycle perspective on sleep investment. The literature shows that sleep affects productivity, earnings, health, and human capital accumulation (Biddle and Hamermesh,1990; Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019; Nguyen et al., 2024; Giuntella et al., forthcoming; Costa-Font et al., 2024), suggesting that sleep can be viewed as an investment that enhances economic performance. Consistent with this interpretation, Hamermesh and Pfann (2022) provide evidence that individuals respond to productivity incentives by investing more effort in maintaining regular and stable sleep schedules. While this literature primarily focuses on contemporaneous sleep outcomes, including average sleep duration or the variability and volatility of sleep patterns, we examine how sleep trajectories diverge over the life cycle. We extend this literature by showing that sleep trajectories evolve heterogeneously across individuals facing different long-run productivity incentives over the life cycle. While such heterogeneity could arise from many characteristics associated with productivity and career incentives, we focus on physical attractiveness and college education as two particularly important and empirically tractable dimensions. We show that the age-related decline in sleep duration is substantially less negative among attractive individuals and college graduates, consistent with the idea that individuals increasingly preserve sleep as its productivity value rises later in life.

Second, the paper contributes to the economics of beauty. We extend the beauty literature by showing that adolescent attractiveness predicts adult sleep behavior decades later, and that this relationship strengthens systematically over the life cycle. More broadly, our findings suggest that attractiveness shapes not only labor market and social outcomes, but also dynamic patterns of health-investment behavior over adulthood.

Third, the paper contributes to the emerging literature linking sleep and physical appearance. Using longitudinal data and interviewer-rated attractiveness measures, we examine whether sleep predicts subsequent attractiveness after controlling for baseline attractiveness. The results provide little evidence that the main findings are driven by sleep mechanically improving later attractiveness, helping distinguish long-run sleep investment behavior from reverse causality through appearance effects.

Fourth, the paper contributes to broader work on human capital, health capital, and healthy aging. The findings suggest that sleep increasingly operates as a productivity-preserving investment over the life cycle rather than solely as a contemporaneous health input. The fact that the age-related decline in sleep is substantially less negative among attractive individuals and college graduates implies that individuals with stronger long-run productivity incentives preserve sleep more aggressively as they age. This interpretation connects the economics of sleep to broader theories of dynamic health investment, cognitive maintenance, and productive aging.

The remainder of the paper proceeds as follows. Section 2 presents the conceptual framework. Section 3 describes the data and key variables. Section 4 presents the methodology. Section 5 presents the main empirical results and supporting analyses. Section 6 concludes.

2 Conceptual Framework

This section develops a simple life-cycle framework linking individual heterogeneity and adult sleep duration. The framework builds on the economics of sleep literature, which models sleep as a productive activity that improves cognitive functioning, health, and labor productivity (Biddle and Hamermesh, 1990; Gibson and Shrader, 2018). We combine this insight with evidence from the economics of beauty and human capital literatures showing that characteristics such as physical attractiveness (see, e.g., Hamermesh and Biddle, 1994; Scholz and Sicinski, 2015; Stinebrickner et al., 2019) and college education (see, e.g., Becker, 1993; Card, 1999; Autor and Dorn, 2013) shape occupational sorting, earnings trajectories, and career advancement. Formal derivations of the dynamic optimization problem, first-order conditions, and comparative statics are provided in Appendix A.

Consider an individual who allocates time between work, leisure, and sleep over the life cycle. Total available time in period t is normalized to one:

$$1 = h_t + l_t + s_t,$$

where h_t denotes working time, l_t denotes leisure, and s_t denotes sleep duration.

The individual maximizes lifetime utility:

$$U = \sum_{t=0}^{T} \beta^t u(c_t, l_t, s_t),$$

where c_t is consumption, l_t is leisure, and s_t is sleep. Assets evolve according to:

$$A_{t+1} = (1 + r)A_t + w(s_t, \theta_i, t)h_t - c_t,$$

where A_t denotes assets, r is the interest rate, and $w(s_t, \theta_i, t)$ is the wage rate. The parameter θ_i denotes occupational or career type. Higher values of θ_i represent occupations in which the productivity value of maintaining cognitive functioning, executive performance, and health becomes increasingly important over the life cycle.

Sleep improves productivity, such that $\frac{\partial w}{\partial s_t} > 0$, consistent with evidence that sleep enhances cognitive performance, mental well-being, and labor productivity (Gibson and Shrader, 2018; Giuntella et al., forthcoming; Costa-Font et al., 2024). We also assume diminishing marginal productivity returns to sleep, so that $\frac{\partial^2 w}{\partial s_t^2} < 0$.

Motivated by evidence that sleep becomes increasingly important for maintaining cognition and productivity later in life (Cohen et al., 2024; Kim et al., 2013; Miller et al., 2014; Sternberg et al., 2013; Scullin and Bliwise, 2015), we further assume that the productivity return to sleep rises with age, implying $\frac{\partial^2 w}{\partial s_t \partial t} > 0$.

Occupations differ in how the productivity return to sleep evolves over the life cycle. The task-based labor literature argues that professional, managerial, and technical occupations are disproportionately intensive in abstract, non-routine cognitive tasks such as problem-solving, judgment, creativity, and information analysis (Acemoglu and Autor, 2011). Because these tasks rely heavily on cognitive performance, executive functioning, and sustained attention, we assume that the age-related increase in the productivity value of sleep is stronger in occupations with greater cognitive task requirements. Formally, $\frac{\partial^3 w}{\partial s_t \partial \theta_i \partial t} > 0$, where θ_i indexes the cognitive task intensity of the occupation. This assumption can also be interpreted as stating that the marginal productivity loss from insufficient sleep increases more rapidly with age in occupations where cognitive performance is particularly important.

To allow average sleep duration to decline over the life cycle, we decompose sleep into two components:

$$s_t = n(t) + m_t,$$

where $n(t)$ denotes baseline biological sleep needs and m_t denotes sleep chosen for its productivity and health-maintenance value. We assume that biological sleep needs decline with age, such that $n'(t) < 0$. Thus, average sleep duration may fall with age even if the economic value of sleep rises.

The key mechanism operates through occupational sorting. More generally, the framework applies to any source of heterogeneity that affects the likelihood of entering occupations in which productivity depends strongly on cognitive performance, executive functioning, and long-run health maintenance. Let a_i denote such an individual characteristic. Higher values of a_i increase the probability of entering occupations with high values of θ_i. In the empirical analysis, we focus primarily on adolescent physical attractiveness and college education as two important proxies of a_i. Formally, the probability of having a high θ_i,

$$P(\theta_i \text{ high} \mid a_i)$$

is increasing in a_i.

The first-order condition for sleep can be written as:

$$u_s + u_c \frac{\partial w}{\partial s_t} h_t = u_c w(s_t, \theta_i, t).$$

This condition shows that optimal sleep is determined by equating the marginal benefits and marginal costs of sleep. The left-hand side captures the marginal benefits of sleep. The first term represents the direct utility value of sleep, while the second term captures the productivity benefit of sleep through higher wages and improved work performance. The right-hand side captures the marginal cost of sleep, which is the utility cost associated with lower consumption resulting from reduced income when an additional unit of sleep displaces one unit of work time.

The model's central prediction follows from the interaction between occupational sorting and the age-varying productivity return to sleep (see the comparative statics in Appendix A for details). If the marginal productivity return to sleep rises sufficiently strongly with age in high-θ_i occupations, then the marginal effect of occupational type on optimal sleep becomes increasingly positive over the life cycle:

$$\frac{\partial}{\partial t}\left(\frac{\partial s_t^*}{\partial \theta_i}\right) > 0.$$

Let a_i denote a source of individual heterogeneity that affects the probability of entering occupations with high values of θ_i. Higher values of a_i increase the likelihood of sorting into occupations in which productivity depends more strongly on cognitive performance, executive functioning, and long-run health maintenance. Formally,

$$\frac{\partial P(\theta_i \text{ high} \mid a_i)}{\partial a_i} > 0.$$

Combining these conditions yields the prediction that the marginal effect of a_i on sleep duration becomes more positive with age:

$$\frac{\partial^2 s_t^*}{\partial a_i \partial t} > 0.$$

Equivalently, the framework predicts that the age-related decline in sleep duration should be less negative for individuals with higher values of a_i:

$$\frac{\partial^2 s_t^*}{\partial t \partial a_i} > 0.$$

Intuitively, individuals with higher values of a_i are more likely to sort into occupations in which maintaining cognitive functioning, executive performance, and health becomes increasingly important over the life cycle. Because the productivity return to sleep rises with age, and because this increase is stronger in high-θ_i occupations, individuals with higher values of a_i face increasingly strong incentives to preserve sleep over the life cycle.

3 Data

The analysis uses the public-use files from the National Longitudinal Study of Adolescent to Adult Health (Add Health), a widely used nationally representative longitudinal survey of U.S. adolescents (Carolina Population Center, nd). The baseline survey (Wave I) was conducted during the 1994–1995 school year and sampled students enrolled in grades 7–12, corresponding roughly to ages 12–18. Respondents were subsequently re-interviewed in 1996 (Wave II), 2001–2002 (Wave III), 2008 (Wave IV), 2016–

2018 (Wave V), and 2023–2024 (Wave VI) (Harris, 2013; Carolina Population Center, nd). The project combines respondent survey files with the corresponding public-use weight files for Waves I through VI. Wave I supplies the baseline attractiveness measure and pre-determined background controls. The main adult sleep analyses use follow-up outcomes from Waves III through VI, allowing respondents to be observed from early adulthood into early midlife. We also report Wave II sleep specifications to provide a fuller life-cycle perspective.

As our hypothesis centers on life-cycle patterns in sleep, the age distribution of respondents across waves is particularly important for the analysis. In the samples summarized in Table 1, the mean age is approximately 16 in Wave II, 22 in Wave III, 28 in Wave IV, 37 in Wave V, and 44 in Wave VI, with an age range of roughly 9 to 10 years within each wave.

3.1 Attractiveness

Conceptually, physical attractiveness can be viewed as containing both relatively stable and behaviorally influenced components. Some determinants of attractiveness are largely inherited or fixed early in life, while others may evolve through behaviors and health investments, including sleep itself. This creates an important empirical challenge because contemporaneous measures of adult attractiveness may partly reflect adult sleep behavior itself. To reduce these reverse-causality concerns, the analysis measures attractiveness during adolescence, prior to the realization of the adult sleep outcomes examined in the paper. The framework therefore focuses on underlying early attractiveness differences across individuals rather than contemporaneous appearance, while using adolescent interviewer-rated attractiveness as a proxy for predetermined attractiveness differences across individuals.[1]

The key explanatory variable is interviewer-rated physical attractiveness at Wave I. At the end of the Wave I interview, interviewers were asked, “How physically attractive is the respondent?” The public-use response scale ranges from very unattractive to very attractive. The main measure, *Attractive, Wave 1*, is an indicator equal to one if the interviewer rated the respondent as attractive or very attractive and zero if the interviewer rated the respondent as very unattractive, unattractive, or about average. The distributions of interviewer-rated attractiveness are broadly similar across waves and closely resemble

[1]We acknowledge that adolescent attractiveness may still partly reflect demographic characteristics and behavioral factors formed earlier in life. We address these concerns in the empirical analysis by controlling for a rich set of background characteristics and by conducting additional robustness checks.

those reported in earlier studies using Add Health attractiveness measures (Chung and Zhang, 2025; Chung et al., 2025).

3.2 College Education

College education is the second key explanatory variable. It provides a conventional measure of human capital and long-run productivity incentives, complementing the attractiveness measure. The analysis uses a wave-specific indicator for whether the respondent has completed a college degree or more by the interview date. In Wave III, the measure is based on highest grade completed; in Waves IV, V, and VI, it is based on the adult educational-attainment questions. The indicator equals one for completed college or higher and zero for less than completed college. Wave II is set to zero because respondents are still too young for adult college completion to be a meaningful realized outcome. This construction allows college status to evolve over early adulthood while preserving the interpretation of the variable as completed higher education in the adult waves.

In the empirical specifications, college education enters both as a control and as a parallel source of heterogeneity in the age-interaction models. The coefficient on the college-by-age interaction tests whether the age profile of sleep differs for college graduates in the same direction predicted for more attractive respondents. The college estimates are not interpreted as causal returns to education; rather, they serve as a comparison based on a more standard marker of human capital, occupational sorting, and long-run productivity incentives.

3.3 Sleep Outcomes

The primary sleep outcome is usual sleep duration in hours. The measure is harmonized across waves using the available Add Health sleep questions. Waves II, V, and VI include direct questions on typical sleep hours, asking how many hours of sleep the respondent usually gets per day or night. Waves III and IV instead ask separate usual bedtimes and wake times for work or school days and for days off; for these waves, sleep duration is constructed as the elapsed time between reported bedtime and wake time, allowing sleep to cross midnight. The baseline harmonized measure uses workday sleep duration in Waves III and IV because it is conceptually closer to the usual sleep-duration questions asked in Waves II, V, and VI and is therefore more comparable across waves. As a robustness check, the appendix also reports alternative specifications using the average of workday and off-day sleep duration in Waves III and IV.

All reported main sleep-duration tables use trimmed sleep measures. Specifically, continuous sleep duration is trimmed within each sex-by-wave group by excluding observations outside the weighted 5th to 95th percentile range before estimation. This trimming reduces the influence of extreme reported sleep values and keeps the continuous outcome comparable across survey waves and sex-specific sleep distributions. The same trimming rule is applied to the harmonized usual/workday sleep measure and to the workday and off-day sleep measures.

The extensive-margin sleep outcomes are indicators for short and long sleep. To preserve comparability across sex and survey waves, these indicators are defined using group-specific percentile cutoffs rather than fixed hour thresholds. After trimming the continuous sleep-hour measure, short sleep is defined as an indicator for respondents in the bottom quintile of the relevant sleep distribution, while long sleep is defined as an indicator for respondents in the top quintile. Accordingly, the short- and long-sleep measures reported in the tables are recalculated within the trimmed analysis sample.

3.4 Mental Health and Trouble-sleeping

We also construct measures of sleep difficulties using the Add Health sleep-problem items. The mechanism analyses focus on Waves IV–VI, where the response scales can be harmonized to a common 0–4 frequency measure. In Wave IV, respondents are asked how often they had trouble falling asleep during the previous four weeks. In Waves V and VI, respondents are asked how often, during the previous four weeks, they had trouble falling asleep or staying asleep through the night, such as waking repeatedly during the night or earlier than intended.[2] Using these items, we construct indicators for reporting sleep difficulties at least once per week, at least three times per week, and at least five times per week. Earlier waves also contain sleep-related questions, but the Wave III item asks how often respondents fell asleep when they should have been awake during the previous seven days and is therefore not comparable to the sleep-difficulty measures used here.

[2] In Wave IV, respondents are asked, "How often did you have trouble falling asleep?" In Waves V and VI, respondents are asked, "Over the past 4 weeks, how often did you have trouble falling asleep or staying asleep through the night—for example, waking up several times during the night or earlier than planned?" Response categories are "Never in the past four weeks," "Less than once a week," "1 or 2 times a week," "3 or 4 times a week," and "5 or more times a week."

For mental health outcomes, Wave VI asks respondents whether a doctor, nurse, or other health-care provider has ever told them that they had depression, generalized anxiety disorder, or panic attacks/panic disorder. We use these responses to construct indicators for ever having been diagnosed with each condition. Respondents reporting a lifetime diagnosis are then asked whether they currently have the condition. We use these follow-up responses to construct current-condition indicators, coding respondents without a lifetime diagnosis as zero. This approach yields full-sample prevalence measures for current depression, anxiety, and panic disorder.

3.5 Controls, Weights, and Samples

All specifications use the relevant public-use survey weights. Single-wave specifications use the wave-specific public-use weight, while pooled specifications apply the corresponding weight to each person-wave observation. Baseline controls include biological sex, U.S.-born status, age and age squared, birth weight and its square, race and Hispanic-origin indicators, Wave I household income, marital and cohabitation status, and child controls when available.

The child measure is wave-specific. Wave III uses the number of children under age six in the household; Wave IV uses the respondent's reported number of children; Wave V uses the number of biological children; and Wave VI adds newly reported biological children to the Wave V count where available.

Some appendix specifications additionally control for Wave I interviewer assessments of the dwelling and neighborhood, as well as baseline self-assessed health and psychosocial measures. Table 1 reports summary statistics for the main variables across survey waves.[3] Several patterns are worth noting.

First, the proportion of respondents rated as attractive in Wave I remains relatively stable across waves, at around one-half of the sample, and the male–female composition also changes little over time. This stability is reassuring because it suggests that the later-wave samples do not exhibit substantial compositional shifts along these dimensions. At the same time, we cannot rule out the possibility that interviewer-rated attractiveness partly reflects subjective interviewer-specific rating standards rather than purely underlying differences across respondents.

Second, sleep duration measures differ across waves because of differences in survey design. In Waves III and IV, sleep duration is constructed from reported sleep and wake times, whereas in the remaining

[3] More detailed wave- and sex-specific summary statistics are provided in Online Appendix Tables A1–A5.

waves it is based on direct questions about sleep duration. Consistent with this difference, mean sleep duration is higher in Waves III and IV, and the dispersion of sleep duration is also noticeably larger in Waves II–IV than in later waves.

Third, the lagged sleep variables refer to sleep outcomes measured in the previous survey wave. For example, in Panel B, "Sleep hours, lagged" corresponds to respondents' Wave II sleep duration for individuals later observed in the Wave III sample. Analogous definitions apply to the lagged sleep measures in subsequent waves.

Fourth, the child measures are not fully comparable across waves. In particular, Wave III records the number of children under age six in the household, whereas later waves measure respondents' own children more directly. For this reason, we estimate pooled-wave regressions both including and excluding Wave III.

Fifth, the share of college degree holders rises substantially across waves, increasing from about 16 percent in Wave III to roughly 45 percent in Wave VI. Part of this increase likely reflects life-cycle educational attainment rather than attrition alone. In particular, some respondents were still of traditional college age in Wave III and had not yet completed their degrees, while others may have obtained college degrees later through continuing education. Nevertheless, these factors do not rule out the possibility of non-random longitudinal attrition or selective sample retention, since more educated respondents may also be more likely to remain in the survey at later waves.

Finally, the summary statistics also indicate a broad decline in sleep duration across adulthood, consistent with the life-cycle patterns emphasized in the conceptual framework. This pattern motivates our focus on whether attractiveness and college education are associated with systematically different sleep trajectories over adulthood.

We address these potential concerns in the methodology and results sections.

4 Methodology

The conceptual framework predicts that the relationship between attractiveness and sleep should become increasingly positive with age because the productivity value of sleep rises over the life cycle, particularly for individuals facing stronger long-run productivity incentives. The framework also predicts a similar age profile for college degree holders. These predictions imply that attractiveness and college education may exhibit only modest associations with sleep at younger ages, but increasingly positive associations at older ages. Because the age range observed within each survey wave is relatively narrow—approximately 9 to 10 years—we first estimate and compare baseline wave-specific specifications for descriptive motivation, and then estimate pooled age-interaction specifications to directly test whether the attractiveness–sleep and college–sleep relationships become increasingly positive over the life cycle.

The empirical analysis relates interviewer-rated attractiveness in adolescence to sleep outcomes observed in adulthood. The baseline wave-specific specification is

$$Y_{iw} = \beta_1 Attr_{i1} + \beta_2 College_{iw} + X'_{iw}\gamma + \mu_{r(i)} + \varepsilon_{iw}, \tag{1}$$

where Y_{iw} denotes a sleep outcome for individual i in wave w, $Attr_{i1}$ is the Wave I indicator for being rated attractive or very attractive, $College_{iw}$ is an indicator for completed college degree or higher by wave w, X_{iw} is the vector of controls described above, and $\mu_{r(i)}$ denotes Wave I interviewer fixed effects. The main outcomes are sleep hours, short sleep, and long sleep as defined in the data section. As respondents age across survey waves, the conceptual framework predicts that β_1 and β_2 should become more positive in later waves.

However, directly estimating age interactions within separate wave-specific specifications is not ideal because the age range within each wave is relatively narrow, generally spanning fewer than ten years. Such limited within-wave variation is insufficient to capture the broader life-cycle patterns emphasized by the conceptual framework. The wave-specific estimates should therefore be interpreted primarily as descriptive or motivating evidence. To more directly examine whether the marginal effects of attractiveness and college education on sleep become increasingly positive over the life cycle, we next estimate age-interaction specifications using data pooled across the adult waves, thereby exploiting substantially broader age variation than is available within any single wave.:

$$\begin{aligned} Y_{iw} = {} & \beta_1 Attr_{i1} + \beta_2 College_{iw} + \delta_1 (Attr_{i1} \times Age_{iw}) \\ & + \delta_2 (College_{iw} \times Age_{iw}) + X'_{iw}\gamma + \mu_{r(i)} + \tau_w + \varepsilon_{iw}, \end{aligned} \tag{2}$$

where τ_w are wave indicators. The coefficient δ_1 tests whether the relationship between teenage attractiveness and adult sleep becomes more positive as respondents age, while δ_2 tests whether the sleep profile of college degree holders also becomes increasingly positive with age. Age enters linearly in the interaction specifications and is interacted with both attractiveness and college degree.

The college interaction serves as a useful comparison because college education provides a more conventional measure of human capital, occupational sorting, and long-run productivity incentives. Parallel age-interaction patterns for attractiveness and college education would therefore support the broader interpretation that individuals with stronger long-run productivity incentives increasingly preserve sleep as they age.

The first concern in our analysis is potential reverse causality, as sleep duration itself may influence perceived attractiveness. To address this issue, attractiveness is measured during adolescence, long before the adult sleep outcomes examined in the main analysis.[4] Measuring attractiveness prior to the adult sleep outcomes helps mitigate concerns that contemporaneous sleep behavior directly influences measured attractiveness and instead allows the analysis to examine how early-life attractiveness predicts subsequent sleep trajectories over the life cycle. This timing is particularly important because adult attractiveness may itself partly reflect accumulated health investments and behaviors, including sleep.

A related concern is that adolescent attractiveness may proxy not only for relatively persistent physical attributes, but also for early-life psychological traits or investments—such as confidence, self-esteem, health or sociability—that continue to shape behavior into adulthood. These underlying characteristics could influence both later educational attainment and adult sleep behavior, implying that the Wave I attractiveness measure may partly capture broader psychological endowments rather than physical appearance alone, and may therefore still be potentially endogenous. Another related potential issue is that interviewer's rating on respondent's attractiveness may be affected by the social background of the respondent. To mitigate these concerns, the Online Appendix reports additional specifications that control for several Wave I proxy measures related to respondents' confidence, social integration, and neighborhood environment. Specifically, these controls include indicators for whether respondents report having many good qualities, feeling socially accepted, and believing they have much to be proud of, as well as interviewer assessments of neighborhood conditions, including whether most buildings on the

[4] We use the Wave I attractiveness measure rather than the Wave II measure because Wave II excluded respondents who were in grade 12 during Wave I, which reduces sample size and longitudinal sample continuity.

street are well maintained and the interviewer's level of concern regarding safety at the respondent's home.[5]

Another central empirical challenge in studying attractiveness is that beauty is inherently subjective and may partly reflect interviewer-specific rating standards rather than underlying differences across respondents. As discussed in the data section, the proportion classified as attractive remains relatively stable across waves, which is reassuring from a compositional perspective, but the interviewer-rated nature of the measure still raises concerns about systematic differences in rating tendencies across interviewers. To address this concern, following the literature (Mocan and Tekin, 2010; Green et al., 2023; Chung et al., 2025; Chung and Zhang, 2025, forthcoming) all specifications absorb Wave I interviewer fixed effects. Because attractiveness is interviewer-assessed, these fixed effects absorb permanent differences in interviewer rating standards, so the attractiveness coefficients are identified from comparisons among respondents evaluated by the same interviewer.

All regressions are estimated using the relevant public-use Add Health survey weights. Single-wave specifications cluster standard errors by Wave I interviewer, while pooled specifications cluster by Wave I interviewer, respondent, and interview year. Clustering by Wave I interviewer accounts for the possibility that interviewer-rated attractiveness partly reflects interviewer-specific standards rather than purely underlying respondent differences, as discussed above. The control variables include biological sex, U.S.-born status, age, birth weight, birth weight squared, race and Hispanic-origin indicators, Wave I household income, and marital and cohabitation status. The baseline adult specifications additionally include wave-specific child controls whenever comparable measures are available.

The pooled-wave specifications additionally include wave fixed effects to account for systematic differences in sleep measurement across survey waves. As discussed in the data section, Waves III and IV construct sleep duration from reported sleep and wake times, whereas the remaining waves rely on direct questions about sleep duration. Consistent with these survey-design differences, average sleep duration and its dispersion are substantially higher in Waves III and IV than in later waves. Including wave fixed

[5]The neighborhood controls also include a set of indicator variables describing the surrounding area and housing environment. Using rural areas as the reference category, area-type indicators distinguish between suburban, urban residential, predominantly retail commercial, and predominantly wholesale or industrial areas. Additional indicators capture the dominant residential structure in the neighborhood, including detached houses, mobile homes, attached houses, subdivided houses, small apartment buildings (2–4 units), apartment buildings with open access (5 or more units), and apartment buildings with restricted access (5 or more units).

effects therefore ensures that the estimated age interactions are not mechanically driven by cross-wave differences in sleep measurement. Standard errors are also clustered by interview year because several survey waves were conducted over multiple calendar years.

Finally, the child measures are not fully comparable across waves. As discussed in the data section, Wave III records the number of children under age six in the household, whereas later waves measure respondents' own children more directly. For this reason, pooled specifications that include Wave III omit child controls, while pooled specifications excluding Wave III include them. Estimating models both with and without Wave III therefore provides a robustness check against inconsistencies in the construction of the child variables across survey waves.

Another empirical challenge is potential non-random longitudinal attrition and changing sample composition across survey waves. The use of longitudinal weights and rich controls reduces concerns about observable attrition, and the pooled specifications additionally absorb common wave effects through wave indicators. However, the estimates could still be affected by selective attrition related to unobserved time-varying determinants of sleep. The summary statistics in Table 1 point to this concern: the share of college degree holders is substantially higher in later analysis samples than in the earlier adult sample. Part of this increase likely reflects life-cycle educational attainment, since some respondents were still of traditional college age in Wave III and others may have completed degrees later through continuing education. Nevertheless, these factors do not rule out the possibility of selective attrition or differential sample retention by education.

We therefore implement two attrition robustness checks for the pooled Table 3 specifications. First, we estimate balanced-panel specifications that restrict the sample to respondents observed in all relevant waves, thereby eliminating compositional changes arising from differential longitudinal retention. Second, we estimate inverse-probability-weighted specifications that reweight observed person-wave observations using predicted retention probabilities based on Wave I characteristics, following standard procedures for addressing attrition under selection on observables (Wooldridge, 2010).

To further assess the interpretation of the main findings, we next examine several mechanisms implied by the conceptual framework. The framework predicts that the increasingly positive attractiveness–sleep and college–sleep relationships over the life cycle operate through productivity incentives and the growing value of maintaining cognitive performance and health at older ages. To examine whether the pattern is tied to productivity incentives, we first estimate the associations between Wave I attractiveness, college degree attainment, and adult labor-market outcomes. We then re-estimate the sleep models separately for workers and non-workers. If maintaining productivity is the primary mechanism, the increasingly positive attractiveness–sleep and college–sleep gradients with age should be stronger among workers.

To examine the alternative hypothesis that attractive individuals or college degree holders sleep more because they experience better mental health or fewer sleep difficulties, we estimate analogous models for Wave VI mental-health diagnoses and current mental-health conditions, as well as for trouble falling asleep across waves.

Although these design choices and robustness checks help address several important empirical concerns, the main estimates should still be interpreted as conditional associations rather than causal effects of attractiveness or college education, since neither characteristic is randomly assigned. Nevertheless, we reject several competing hypotheses, and the identifying variation remains informative for testing whether the observed life-cycle pattern of sleep is consistent with the proposed framework.

5 Empirical Results

Before proceeding to the main results, it is important to verify that attractiveness and college attainment are associated with occupational sorting, particularly into occupations that place greater demands on cognitive and vigilance-related functions, as implied by our proposed mechanism. Appendix Table A6 provides a direct check of the occupational-sorting premise behind the mechanism. Across Waves III–VI, college graduates are consistently more likely to work in occupations classified as high overall and high cognitive task-demand jobs. Wave I attractiveness is also positively associated with sorting into high overall task-demand occupations in several waves, although the estimates are less uniform across the cognitive and vigilance measures. These patterns support the interpretation that the two main sources of heterogeneity used in the paper are related to occupational sorting into jobs where cognitive performance, executive functioning, and sustained attention may be especially valuable.[6]

[6]The three dependent variables in Appendix Table A6 are occupation-level indicators constructed from the occupational-task approach used in the task-based labor literature (Acemoglu and Autor, 2011; Autor and Dorn, 2013) and in the beauty-and-job-tasks literature (Stinebrickner et al., 2019). We first map Add Health occupation codes in Waves III–VI to broad occupation groups and merge them to task measures from the O*NET database. The cognitive index averages measures related to reasoning, problem solving, critical thinking, judgment, analyzing information, and making decisions. The vigilance index

5.1 Attractiveness and Adult Sleep over the Life Cycle

Table 2 provides the first evidence on the paper's main hypothesis. Panel A reports the Wave II results and shows little evidence that Wave I attractiveness predicts longer sleep at younger ages. None of the attractiveness coefficients are statistically significant, although the coefficients on sleep duration and long sleep are negative. At these younger ages, the relationship between attractiveness and sleep appears weak and imprecisely estimated.

Panels B and C report the Wave III workday and off-day results, respectively, while Panels D and E present the corresponding estimates for Wave IV. In both waves, the workday measures are of primary interest because they are conceptually closer to the usual sleep-duration measures available in the later waves and are therefore more comparable across the life cycle.

Panel B provides some suggestive evidence of a negative association between attractiveness and sleep in early adulthood. In particular, attractiveness is negatively associated with long sleep, and the coefficient is statistically significant at the 1 percent level. Being rated as attractive in Wave I is associated with a 5.2 percentage-point reduction in the probability of long sleep on workdays in Wave III. The coefficient for sleep duration is also negative, although statistically insignificant, while the coefficient for short sleep is close to zero.

Panel D reports the Wave IV workday estimates. Relative to Wave III, the evidence of a negative attractiveness–sleep relationship becomes weaker and more mixed. Although the coefficients for sleep hours and long sleep remain negative, neither is statistically significant. The coefficient for short sleep is also negative. Overall, the Wave IV results suggest little systematic association between attractiveness and sleep duration at this stage of adulthood. The off-day estimates in Panels C and E are similarly imprecise and do not display a clear or consistent pattern.

The results change substantially in later adulthood. Panel F shows that by Wave V, attractiveness is positively associated with sleep duration. Attractive respondents sleep significantly longer, are less likely to experience short sleep, and are more likely to experience long sleep. Specifically, being rated as

averages measures related to selective attention, time sharing, perceptual speed, monitoring, exactness, and consequence of error. The overall index averages the cognitive and vigilance indexes. Each dependent variable equals one if the occupation group is in the top quartile of the corresponding index and zero otherwise. Because the occupational classifications available in Add Health differ across waves, the resulting occupation groups are not directly comparable over time, although the task indexes are constructed using the same procedure in every wave.

attractive in adolescence is associated with approximately 0.16 additional hours of sleep, a 6.5 percentage-point reduction in the probability of short sleep, and a 4.9 percentage-point increase in the probability of long sleep. Panel G shows a very similar pattern in Wave VI: attractive respondents continue to sleep longer, are significantly less likely to be short sleepers, and are more likely to be long sleepers. Taken together, these estimates are consistent with our central prediction that the attractiveness–sleep relationship becomes increasingly positive over the life cycle.

The college coefficients display a broadly similar pattern. In the earlier adult waves, college completion is either weakly related or negatively related to sleep outcomes, particularly for long sleep. However, by Waves V and VI, college graduates sleep longer and are substantially less likely to experience short sleep. The emergence of a parallel age gradient for both attractiveness and college education is important because college education represents a more conventional measure of human capital and long-run productivity incentives. The similarity between the two patterns therefore supports the interpretation that individuals facing stronger long-run productivity incentives increasingly preserve sleep as they age.

There are also several notable sex differences across waves. Female respondents generally report longer sleep duration than males in the later adult waves and are often more likely to experience long sleep. These patterns suggest that potential gender heterogeneity may also be important for understanding the attractiveness–sleep relationship. We therefore further investigate whether the life-cycle patterns predicted by our hypothesis differ by biological sex in the pooled age-interaction specifications.

Columns 4–6 of Table 3 tests the life-cycle hypothesis more directly using pooled age-interaction specifications. Panel A pools Waves IV–VI and includes child controls, while Panel B pools Waves III–VI and omits child controls because the child variables are not fully comparable in Wave III.

Columns 1–3 first report specifications without age interactions. In these pooled average estimates, Wave I attractiveness exhibits little overall association with adult workday sleep outcomes. By contrast, college degree is associated with a significantly lower probability of short sleep, although its associations with sleep hours and long sleep are generally small. These non-age-interacted estimates suggest that averaging across adulthood obscures substantial heterogeneity in the attractiveness–sleep and college–sleep relationships over the life cycle.

Columns 4–6 then allow the effects of both Wave I attractiveness and college degree to vary with age.

The results reveal a clear and highly consistent life-cycle pattern. In Panel A, the interaction between attractiveness and age is positive for sleep hours and long sleep and negative for short sleep, with all coefficients statistically significant at the 1 percent level. The same pattern also appears for the college-age interactions. These estimates strongly support the prediction of the conceptual framework that individuals facing stronger long-run productivity incentives increasingly preserve sleep as they age.

The magnitudes of the coefficients are also economically meaningful. In Panel A, the coefficient on Attractive $\times$ Age in the sleep-hours specification is 0.011. This implies that the sleep-duration difference between attractive and non-attractive respondents increases by roughly 0.11 hours over a 10-year age increase, equivalent to approximately 6.6 additional minutes of sleep per night. Over the roughly 15-year age difference between the average respondents in Waves IV and VI, the implied sleep gap widens by approximately 0.17 hours, or about 10 additional minutes of sleep per night. Similarly, the coefficient on Attractive $\times$ Age in the short-sleep specification is -0.005, implying that attractive respondents become around 5 percentage points less likely to experience short sleep over a 10-year age increase relative to non-attractive respondents. Meanwhile, the corresponding coefficient for long sleep is 0.007, implying an approximately 7 percentage-point relative increase in the probability of long sleep over the same age span.

The estimated coefficients also imply that the attractiveness–sleep relationship shifts from negative to positive as respondents move through adulthood. In Panel A, the main effect of attractiveness on sleep hours is -0.336, while the interaction coefficient is 0.011. These estimates imply that the association between attractiveness and sleep duration becomes positive at approximately age 31 ($0.336/0.011 \approx 30.5$). Similarly, the long-sleep relationship turns positive at around age 32, while the short-sleep relationship becomes increasingly negative throughout adulthood. These turning points align closely with the descriptive evidence in Table 2, where the attractiveness–sleep relationship is weakly negative or negligible in the younger adult waves but becomes clearly positive by Waves V and VI.

The college-age interactions are quantitatively similar and economically important as well. In Panel A, the coefficient on College Degree $\times$ Age is 0.015 in the sleep-hours specification, implying that the sleep-duration advantage associated with college education rises by approximately 0.15 hours over a 10-year age increase, or roughly 9 additional minutes of sleep per night. The corresponding short-sleep interaction coefficient of -0.003 indicates that college graduates become increasingly less likely to experience short sleep as they age, while the positive long-sleep interaction suggests a growing tendency toward longer sleep durations later in adulthood. Using the sleep-hours estimates, the implied turning point for the college–sleep relationship occurs at approximately age 32, again indicating that the association becomes increasingly positive in later adulthood.

Panel B provides a useful robustness check by extending the pooled sample to include Wave III while omitting child controls. Reassuringly, the estimated interaction coefficients remain highly comparable to those in Panel A. For example, the attractiveness–age interaction for sleep hours is 0.008 in Panel B, compared with 0.011 in Panel A, while the corresponding long-sleep interaction coefficients are 0.005 and 0.007, respectively. Likewise, the college–age interaction coefficients remain very similar across the two pooled samples. The stability of these estimates across specifications provides additional support that the observed life-cycle gradients are not driven by the inclusion of Wave III or by differences in the treatment of child controls.[7]

One concern is that the results may be sensitive to the measurement of attractiveness. To examine this possibility, we re-estimate Table 3 using alternative attractiveness measures. In particular, we replace the baseline binary attractiveness indicator with separate indicators for respondents rated as "attractive" and "very attractive" in the pooled workday specifications. The results remain qualitatively unchanged. Moreover, the coefficients on the "very attractive" indicator and its interaction with age have the same signs as those for the broader attractiveness measure but are larger in magnitude, further supporting the hypothesis that individuals with higher attractiveness increasingly preserve sleep as they age (see Appendix Table A8).

Although measuring attractiveness in Wave I helps mitigate reverse-causality concerns, we cannot rule out the possibility that adolescent attractiveness partly captures early-life psychological traits or invest-

[7] In Table 2, the Wave III and Wave IV sleep measures use workday sleep duration rather than off-day sleep duration because workday sleep is conceptually closer to the "usual sleep duration" measures available in the other waves and is therefore more comparable across the life cycle. As a robustness check, we also re-estimate the Panel A pooled specifications using the average of workday and off-day sleep duration in Waves III and IV. The results remain very similar (see Panel A of Table A7a). In addition, because Table 3 focuses primarily on the adult waves (III–VI), we further re-estimate the pooled specifications after including Wave II, when respondents were still adolescents. The resulting estimates again remain highly similar to the baseline findings reported in Table 3 (see Panel B of Table A7a). To examine whether the pooled age-interaction results differ by biological sex, we also re-estimate Table 3 by additionally interacting the attractiveness–age and college–age terms with the female indicator (see Table A7b). The attractiveness–age and college–age interaction terms remain similar in sign and statistical significance, while the additional female interaction terms are generally insignificant. The main exception is the female × attractiveness × age interaction in Panel C. Nevertheless, the overall attractiveness–age effect remains positive for both males and females.

ments—such as confidence, self-esteem, health, or sociability—that continue to shape behavior into adulthood. In addition, interviewer ratings of attractiveness may partly reflect respondents' social background or neighborhood environment rather than physical appearance alone. To address these concerns, we re-estimate Table 3, additionally controlling for several Wave I psychosocial and neighborhood characteristics. Specifically, we include indicators for whether respondents report having many good qualities, feeling socially accepted, and believing they have much to be proud of, as well as interviewer assessments of neighborhood conditions, including whether most buildings on the street are well maintained and the interviewer's level of concern regarding safety at the respondent's home. The results, reported in Table A9, remain highly similar to the baseline findings.

Another concern is that the pooled sample composition may change across waves because respondents with lower education or other disadvantages are more likely to attrit from the longitudinal survey. Appendix Table A10 addresses this concern by re-estimating Table 3 using balanced panels that require respondents to be observed in every wave included in each pooled sample. Appendix Table A11 provides a complementary inverse-probability-weighted robustness check. In both cases, the age-interaction patterns remain clearly visible.

A related concern is that college completion may partly reflect earlier sleep patterns during adolescence. To address this issue, Appendix Table A12 re-estimates the pooled college-age specifications while additionally controlling for Wave I sleep hours and Wave I short- and long-sleep indicators. The attractiveness–age and college–age interaction patterns remain highly similar to the baseline results. Overall, these robustness checks further support the comparative static emphasized in the conceptual framework.

Taken together, these additional results show that the main findings are not driven by a single sex, the binary definition of attractiveness, balanced-panel sample construction, selective attrition, or the omission of additional Wave I background characteristics.

5.2 Work Status

The conceptual framework emphasizes productivity incentives: attractiveness and college education matter for sleep because they increase the returns to maintaining productivity and performance, particularly among individuals attached to the labor market. Consequently, the framework predicts that the positive effects of attractiveness and college education on sleep duration should be strongest among those who are working.

Our data contain direct information on employment status in Waves III, V, and VI. In Wave IV, however, respondents are instead asked whether they worked for pay at least 10 hours per week. Because these measures are not directly comparable across waves, pooled specifications are less appropriate for this analysis. We therefore adopt a wave-specific approach.

Table 4 reports separate estimates for the working group (respondents who are employed in Waves III, V, and VI, or who worked at least 10 hours per week in Wave IV) and the comparison group (respondents who are not employed in Waves III, V, and VI, or who worked fewer than 10 hours per week in Wave IV). Consistent with the predictions of the conceptual framework, the coefficients for both attractiveness and college education become increasingly positive and statistically significant across later waves among working respondents. In contrast, the corresponding coefficients for the comparison group generally do not display a similar pattern and remain statistically insignificant in most specifications. While this evidence is consistent with the productivity-incentive mechanism, the weaker results among non-workers should be interpreted cautiously, as the smaller sample sizes in this group may reduce statistical power.[8]

5.3 Alternative Hypothesis: Health-Based Explanations

An alternative explanation for our findings is that attractive individuals and college graduates sleep longer because they experience fewer sleep difficulties, potentially as a consequence of better mental health. Since our main results show that the effects of attractiveness and college attainment on sleep duration become stronger with age, this explanation implies that the negative associations between attractiveness or college attainment and sleep difficulties should likewise become increasingly pronounced as individuals age. In other words, if reduced sleep difficulties are the mechanism underlying our findings, attractive individuals and college graduates should become progressively less likely to report sleep problems

[8] As an additional test of the productivity-incentive mechanism, we estimate wave-specific sleep regressions that replace Wave I attractiveness and college attainment with an indicator for employment in a high overall task-demand occupation. The estimates, reported in Appendix Table A13, indicate that workers in high task-demand occupations tend to sleep less in earlier waves, but this relationship becomes increasingly positive at older ages, particularly through a reduced likelihood of short sleep. This pattern is consistent with the view that individuals facing greater productivity demands place a higher value on sleep as they age. Because occupational classifications differ across waves and are not directly comparable, the analysis is conducted separately for each wave.

relative to their peers as they grow older.

Table 5 reports estimates for trouble falling asleep or staying asleep through the night. Across Waves IV–VI, attractiveness is not consistently associated with a lower probability of reporting sleep difficulties. In the specifications without age interactions, the coefficient on attractiveness is negative and statistically significant only for the outcome of experiencing sleep difficulties three or more times per week. More importantly, the age-interacted specifications provide some evidence in the opposite direction of the mental-health hypothesis. For the more severe sleep-difficulty measures (three or more times per week and five or more times per week), the coefficients on the Attractive $\times$ Age interaction are positive and statistically significant at the 10% level. These results imply that the association between attractiveness and sleep difficulties becomes less favorable with age, which is difficult to reconcile with our earlier finding that the attractiveness premium in sleep duration increases over the life cycle.

The results for college education are similarly inconsistent with the mental-health explanation. In the specifications without age interactions, college graduates are generally less likely to report trouble falling asleep. However, the age-interacted estimates do not reveal a clear pattern. The coefficient on College Degree $\times$ Age is statistically insignificant for the most severe sleep-difficulty measure (five or more times per week), positive and significant for three or more times per week, and negative and significant for at least once per week. These mixed findings do not align with the strong and consistently increasing college gradient in sleep duration documented in Tables 2 and 3. It is also important to distinguish sleep difficulties from sleep duration. The mental-health hypothesis requires that the increasing attractiveness and college gradients in sleep duration be accompanied by increasingly favorable sleep-quality outcomes as individuals age, a prediction that is inconsistent with the evidence in Table 5. At the same time, sleep difficulties need not translate one-for-one into shorter sleep duration. Individuals facing stronger incentives to preserve sleep may respond by allocating more time and resources to obtaining sleep, even when sleep becomes more difficult. Consequently, the absence of increasingly negative age interactions in the sleep-difficulty regressions undermines the mental-health explanation, while the positive age interactions observed for some sleep-difficulty measures do not necessarily imply that the attractiveness and college gradients in sleep duration should decline with age. Instead, these patterns remain consistent with the sleep-investment mechanism proposed in Section 2.[9]

[9] Appendix Table A14 examines Wave VI indicators for ever being diagnosed with, and currently suffering from, depression, generalized anxiety disorder, and panic attacks or panic disorder. The estimates provide little evidence that Wave I attractiveness

The evidence also allows us to evaluate two broader health-based explanations for the increasing marginal effects of attractiveness and college on sleep duration. A first explanation is that attractive individuals possess superior underlying health endowments or genetic traits that allow them to obtain more sleep throughout life. A similar argument can be made for college graduates if they possess better health knowledge and therefore can manage sleep more efficiently. However, these explanations predict that attractiveness and college education should be positively associated with sleep duration at all ages. This prediction is inconsistent with our main results. In Table 3, the coefficients on attractiveness and college degree are negative, while the interactions between these variables and age are positive. The implied turning points occur at approximately age 31 for attractiveness and age 32 for college education. Thus, attractive individuals and college graduates do not sleep more at younger ages. Instead, their sleep advantage emerges only later in adulthood. This pattern is difficult to reconcile with a simple health-endowment or health-knowledge explanation but is consistent with the life-cycle sleep-investment hypothesis developed in Section 2.

A second explanation focuses on long-run health capital. College graduates may accumulate health advantages over the life cycle because they possess better health knowledge and engage in healthier behaviors. If better health reduces sleep difficulties, college graduates should become increasingly less likely to experience trouble falling asleep as they age. Table 5 provides little support for this mechanism. The estimated interactions between college degree and age are generally weak and inconsistent across sleep-difficulty measures. For the specification based on reporting trouble falling asleep three or more times per week, the interaction coefficient is positive and statistically significant, implying that older college graduates are more likely to report sleep difficulties. More broadly, the estimated patterns do not indicate that college graduates experience systematically fewer sleep difficulties as they age. If anything, some estimates point in the opposite direction. These findings are difficult to reconcile with the hypothesis that superior long-run health explains the increasingly positive college effect on sleep documented in Tables 2 and 3.[10]

is systematically associated with any of these mental-health outcomes. Although college graduates are less likely to report depression and, in some specifications, panic attacks, the patterns are neither uniform across outcomes nor consistent across men and women. Female-interacted specifications lead to the same conclusion regarding attractiveness: the coefficients remain small, statistically imprecise, and inconsistent in sign. Meanwhile, the negative association between college attainment and depression appears to be concentrated among women. Overall, the heterogeneous and inconsistent relationships between attractiveness, education, and mental-health outcomes make it difficult to attribute the robust age-related increases in the attractiveness and college sleep gradients to mental health.

[10]We further estimate the specifications in Table 5, allowing the effects to vary by both age and sex; the results are presented in Appendix Table A15. The findings reveal pronounced sex-specific heterogeneity in the associations between attractiveness,

Taken together, the evidence provides little support for either a health-knowledge explanation or a long-run health-capital explanation. Both mechanisms predict that the sleep advantage of attractive individuals and college graduates should either be present throughout adulthood or operate through increasingly favorable sleep quality as respondents age. Neither prediction aligns well with the empirical evidence. Instead, the results are more consistent with the interpretation that individuals facing stronger long-run productivity incentives increasingly preserve sleep as the productivity value of sleep rises over the life cycle.

5.4 Alternative Hypothesis: Social Gatherings and Sleep Duration

Another potential explanation for our findings is that attractive individuals and college graduates may sleep more because they participate less frequently in social activities that compete with sleep time, particularly later in life. If this mechanism were important, the attractiveness and college gradients in social-gathering behavior should become increasingly negative with age, mirroring the increasingly positive gradients in sleep duration documented in Tables 2 and 3.

Information on social-gathering behavior is available only in Waves III, V, and VI. Consequently, we estimate separate wave-specific regressions, the results of which are reported in Appendix Table A16. The estimates provide little support for the social-gathering hypothesis. Across all three waves, the coefficients on Wave I attractiveness are small in magnitude, statistically insignificant, and display no systematic trend with age. The point estimates remain close to zero throughout, indicating that attractive individuals are neither more nor less likely to participate in social gatherings than their less attractive counterparts. Similarly, the coefficients on college attainment are also small and statistically insignificant in every wave, providing no evidence that college graduates systematically differ in their frequency of social participation.

The female-interacted specifications likewise reveal no meaningful gender differences in these relationships. The Female $\times$ Attractive interaction terms are small and statistically insignificant across all waves, suggesting that the association between attractiveness and social participation does not differ substantially between men and women. This finding is notable because our main results show little evidence that the age profiles of the attractiveness and college effects on sleep duration differ by sex.

education, and sleep difficulties over the life course, casting doubt on the existence of a common health or mental health mechanism driving these relationships.

More broadly, the estimates do not suggest that either attractive individuals or college graduates increasingly reduce their participation in social activities as they age. If anything, the coefficients remain remarkably stable across survey waves. Consequently, the growing attractiveness and college gradients in sleep duration are unlikely to be explained by changes in social-gathering behavior over the life cycle. Instead, the evidence indicates that attractive individuals and college graduates maintain broadly similar patterns of social participation while nevertheless exhibiting increasingly favorable sleep outcomes at older ages.

5.5 Sleep and Subsequent Attractiveness

Table 6 examines whether the relationship could instead reflect sleep affecting later attractiveness. This exercise is an additional reverse-direction check rather than a direct test of our main hypothesis. Panel A uses the shorter-run panel structure before the main adult sleep outcomes: Wave I sleep predicts Wave II attractiveness, and Wave II sleep predicts Wave III attractiveness. Panels B and C extend the check to Wave IV attractiveness, using Wave III workday sleep and Wave III work-off average sleep, respectively. These two Wave IV panels are estimated on a common sample that requires both Wave III sleep measures to be observed. All specifications control for Wave I attractiveness. If sleep strongly improved subsequent interviewer-rated attractiveness, lagged sleep hours or lagged short- and long-sleep indicators should predict later attractiveness conditional on baseline attractiveness and interviewer fixed effects.

The estimates provide little evidence for this reverse channel. In Panel A, lagged sleep hours, lagged short sleep, and lagged long sleep are small and statistically insignificant in the pooled, sex-specific, and sex-interaction specifications. The Wave IV checks reach the same conclusion: neither Wave III workday sleep in Panel B nor Wave III work-off average sleep in Panel C robustly predicts Wave IV attractiveness. By contrast, Wave I attractiveness strongly predicts later attractiveness, as expected. This does not rule out all possible short-run effects of sleep on appearance, but it suggests that the main adult results are not simply a mechanical consequence of earlier sleep changing measured attractiveness.

6 Conclusion

This paper develops and tests a simple life-cycle hypothesis of sleep investment. Motivated by evidence that the cognitive, health, and productivity consequences of insufficient sleep become increasingly severe with age, we argue that sleep should be viewed not only as a contemporaneous health input but also as a productivity-preserving investment whose value rises over the life cycle. The framework predicts that individuals facing stronger long-run productivity incentives will increasingly preserve sleep as they age, leading to widening differences in sleep duration across adulthood.

Using longitudinal data from Add Health, we find strong support for this prediction. Although adolescent attractiveness and college education exhibit only weak relationships with sleep during early adulthood, both characteristics become increasingly positively associated with sleep duration later in life. Attractive individuals and college graduates experience substantially less negative age-related declines in sleep, are increasingly less likely to experience short sleep, and are increasingly more likely to experience long sleep. These patterns emerge consistently across wave-specific and pooled specifications and remain robust to a wide range of alternative specifications and sample restrictions.

Importantly, we do not interpret attractiveness as uniquely important in itself. Rather, attractiveness and college education serve as two distinct empirical examples of a broader mechanism linking long-run productivity incentives and sleep investment. The fact that similar age profiles emerge for both characteristics suggests that the findings are not specific to beauty or education. Instead, they are consistent with the more general proposition that individuals who sort into occupations where cognitive performance, executive functioning, and long-run productivity remain especially valuable increasingly preserve sleep as they age.

Several additional findings support this interpretation. The patterns are strongest among workers, where productivity incentives should be most relevant. By contrast, we find little evidence that the results are driven by mental health, sleep difficulties, social-gathering behavior, or reverse causality operating through sleep-induced changes in attractiveness. Although these analyses cannot establish causality, they help narrow the range of plausible alternative explanations.

More broadly, the results contribute to the economics of sleep by introducing a life-cycle perspective on sleep investment. Existing research has largely focused on the average effects of sleep on productivity, health, and earnings. Our findings suggest that an equally important question concerns who preserves sleep as they age and why. If sleep increasingly functions as a form of productive aging and cognitive maintenance, then differences in incentives and opportunities to maintain sleep may become an important source of inequality later in life.

The paper also raises several directions for future research. While we focus on attractiveness and college education, the framework applies more generally to any characteristic associated with occupational sorting, career incentives, or the long-run returns to cognitive performance and health maintenance. Future work could examine whether similar life-cycle sleep gradients emerge across occupations, income groups, wealth levels, cognitive ability, or other dimensions of human capital. More generally, understanding how individuals adjust sleep behavior in response to changing productivity incentives may provide new insights into the interaction between health investment, labor-market behavior, and successful aging over the life course.

In sum, the evidence suggests that sleep is not merely a biological necessity whose importance remains constant throughout life. Rather, sleep increasingly appears to function as a productive investment that individuals differentially preserve as they age. The widening sleep advantages observed among attractive individuals and college graduates are therefore best interpreted not as evidence about beauty or education per se, but as evidence supporting a broader life-cycle theory of sleep investment.

Table 1: Summary Statistics for Sleep, Attractiveness, Sex, Age, and College

Variable	Obs.	Mean	Std. dev.	Min	Max
Panel A: Wave 2 lagged sleep					
Sleep hours, lagged	4,475	7.922	1.086	6	10
Short sleep, lagged	4,475	0.331	0.471	0	1
Long sleep, lagged	4,475	0.271	0.444	0	1
Attractive, Wave 1	4,475	0.504	0.500	0	1
Female	4,475	0.492	0.500	0	1
Age	4,475	15.946	1.617	12	21
College degree	4,475	0.000	0.000	0	0
Panel B: Wave 3 workday and off-day sleep					
Workday sleep hours	2,996	7.751	1.282	5	12
Short workday sleep	2,996	0.269	0.443	0	1
Long workday sleep	2,996	0.253	0.435	0	1
Off-day sleep hours	2,996	9.023	1.833	6	20
Short off-day sleep	2,996	0.268	0.443	0	1
Long off-day sleep	2,996	0.314	0.464	0	1
Sleep hours, lagged	2,286	7.640	1.126	5	10
Short sleep, lagged	2,286	0.430	0.495	0	1
Long sleep, lagged	2,286	0.377	0.485	0	1
Attractive, Wave 1	2,996	0.525	0.499	0	1
Female	2,996	0.490	0.500	0	1
Age	2,996	21.798	1.827	18	28
College degree	2,996	0.162	0.369	0	1
Panel C: Wave 4 workday and off-day sleep					
Workday sleep hours	3,245	7.605	1.153	5	13
Short workday sleep	3,245	0.283	0.451	0	1
Long workday sleep	3,245	0.200	0.400	0	1
Off-day sleep hours	3,245	8.687	1.575	6	19.5
Short off-day sleep	3,245	0.278	0.448	0	1
Long off-day sleep	3,245	0.220	0.414	0	1
Attractive, Wave 1	3,245	0.530	0.499	0	1
Female	3,245	0.503	0.500	0	1
Age	3,245	28.232	1.816	24	33
College degree	3,245	0.343	0.475	0	1
Panel D: Wave 5 sleep					
Sleep hours	2,906	6.785	0.953	5	9
Short sleep	2,906	0.402	0.490	0	1
Long sleep	2,906	0.252	0.434	0	1
Attractive, Wave 1	2,906	0.515	0.500	0	1
Female	2,906	0.505	0.500	0	1
Age	2,906	36.569	2.032	32	42
College degree	2,906	0.397	0.489	0	1
Panel E: Wave 6 sleep					
Sleep hours	2,245	6.763	0.965	5	9
Short sleep	2,245	0.397	0.489	0	1
Long sleep	2,245	0.243	0.429	0	1
Attractive, Wave 1	2,245	0.533	0.499	0	1
Female	2,245	0.531	0.499	0	1
Age	2,245	44.054	1.914	40	49
College degree	2,245	0.448	0.497	0	1

Table 2: Effects of College Degree and Wave 1 Attractiveness on Sleep Outcomes by Wave (continued on next page)

Variable	Sleep hours (1)	Short sleep (2)	Long sleep (3)
Panel A: Wave 2			
Attractive, Wave 1	-0.053	0.016	-0.027
	(0.051)	(0.022)	(0.021)
Female	-0.296***	0.091***	0.308***
	(0.048)	(0.021)	(0.021)
Observations	3,521	3,521	3,521
Panel B: Wave 3 workday			
Attractive, Wave 1	-0.084	0.008	-0.052***
	(0.060)	(0.022)	(0.019)
Female	0.391***	0.032	-0.008
	(0.068)	(0.023)	(0.023)
College degree	-0.057	0.012	-0.028
	(0.079)	(0.030)	(0.029)
Observations	2,942	2,942	2,942
Panel C: Wave 3 off-day			
Attractive, Wave 1	-0.070	-0.005	-0.031
	(0.090)	(0.022)	(0.023)
Female	-0.070	0.167***	0.001
	(0.088)	(0.023)	(0.024)
College degree	0.072	-0.042	-0.006
	(0.102)	(0.032)	(0.030)
Observations	2,942	2,942	2,942
Panel D: Wave 4 workday			
Attractive, Wave 1	-0.023	-0.023	-0.030
	(0.052)	(0.022)	(0.019)
Female	0.432***	0.040*	0.035*
	(0.055)	(0.021)	(0.020)
College degree	-0.065	-0.045*	-0.051**
	(0.056)	(0.023)	(0.022)
Observations	3,182	3,182	3,182

Table 2: Effects of College Degree and Wave 1 Attractiveness on Sleep Outcomes by Wave (continued)

Variable	Sleep hours	Short sleep	Long sleep
	(1)	(2)	(3)
Panel E: Wave 4 off-day			
Attractive, Wave 1	-0.023	-0.016	-0.011
	(0.069)	(0.020)	(0.019)
Female	0.317***	0.144***	-0.019
	(0.077)	(0.022)	(0.020)
College degree	-0.034	-0.039*	-0.045**
	(0.081)	(0.022)	(0.022)
Observations	3,182	3,182	3,182
Panel F: Wave 5			
Attractive, Wave 1	0.158***	-0.065***	0.049**
	(0.048)	(0.024)	(0.022)
Female	0.136***	-0.016	0.101***
	(0.052)	(0.027)	(0.022)
College degree	0.109**	-0.094***	-0.019
	(0.054)	(0.028)	(0.024)
Observations	2,828	2,828	2,828
Panel G: Wave 6			
Attractive, Wave 1	0.148**	-0.079**	0.060**
	(0.060)	(0.031)	(0.025)
Female	0.254***	-0.058*	0.111***
	(0.061)	(0.033)	(0.025)
College degree	0.202***	-0.089***	0.034
	(0.063)	(0.032)	(0.028)
Observations	2,163	2,163	2,163
Control variables	✓	✓	✓
Interviewer fixed effects	✓	✓	✓

Notes: The table reports selected coefficient estimates from weighted regressions by wave and sleep outcome, with standard errors in parentheses. The Wave 2 panel uses the Wave 2 sleep measures; Wave 3 and Wave 4 distinguish workday and off-day sleep; Waves 5 and 6 use the available adult sleep measures. Control variables include biological sex, US-born status, age, age squared, birth weight, birth weight squared, race and Hispanic-origin indicators, family-formation controls, and log Wave 1 household income. Family-formation controls are cohabitation and marriage status; child controls are included where available. Standard errors are clustered at the interviewer level.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Pooled Workday Sleep-Duration Estimates with Attractiveness and College-Age Specifications

Variable	Non-age-interacted			Age-interacted		
	Hours	Short	Long	Hours	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Waves 4 to 6 pooled, workday measure						
Attractive, Wave 1	0.038	-0.025	0.009	-0.336***	0.163***	-0.226***
	(0.047)	(0.020)	(0.025)	(0.050)	(0.032)	(0.029)
Attractive, Wave 1 × Age				0.011***	-0.005***	0.007***
				(0.001)	(0.001)	(0.001)
College degree	0.046	-0.066**	-0.015	-0.484***	0.048	-0.203***
	(0.093)	(0.021)	(0.028)	(0.098)	(0.053)	(0.014)
College degree × Age				0.015***	-0.003*	0.005***
				(0.003)	(0.001)	(0.001)
Age	-0.040***	-0.006	-0.012**	-0.027***	0.008***	-0.009**
	(0.007)	(0.004)	(0.005)	(0.007)	(0.002)	(0.003)
Observations	8,396	8,396	8,396	8,396	8,396	8,396
Panel B: Waves 3 to 6 pooled, workday measure, no child controls						
Attractive, Wave 1	-0.001	-0.017	-0.008	-0.253***	0.090**	-0.158***
	(0.036)	(0.013)	(0.017)	(0.036)	(0.031)	(0.028)
Attractive, Wave 1 × Age				0.008***	-0.004***	0.005***
				(0.001)	(0.001)	(0.001)
College degree	0.020	-0.061***	-0.023	-0.500***	0.059**	-0.200***
	(0.064)	(0.014)	(0.022)	(0.065)	(0.022)	(0.025)
College degree × Age				0.016***	-0.004***	0.005***
				(0.002)	(0.001)	(0.001)
Age	-0.081***	0.000	-0.028***	-0.033***	0.007***	-0.011***
	(0.015)	(0.004)	(0.007)	(0.005)	(0.002)	(0.002)
Observations	11,392	11,392	11,392	11,392	11,392	11,392
Control variables	✓	✓	✓	✓	✓	✓
Wave indicators	✓	✓	✓	✓	✓	✓

Notes: The table reports weighted pooled workday sleep regressions, with standard errors in parentheses. Panel A pools Waves 4 to 6 and includes number of children; Panel B pools Waves 3 to 6 and omits child controls. Columns 1–3 report non-age-interacted specifications; columns 4–6 report specifications that interact Wave 1 attractiveness and college degree with age. Control variables include biological sex, US-born status, age, birth weight, birth weight squared, race and Hispanic origin indicators, cohabitation, marriage, log Wave 1 household income, and wave indicators. Standard errors are clustered by respondent and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: College Degree, Wave 1 Attractiveness and Sleep Outcomes by Work Status (continued on next page)

Variable	Work-status group			Comparison group		
	Hours	Short	Long	Hours	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Wave 3 workday sleep, by work status						
Attractive, Wave 1	-0.074	-0.006	-0.047**	-0.167	0.023	-0.109**
	(0.067)	(0.027)	(0.021)	(0.141)	(0.041)	(0.053)
Female	0.404***	0.020	-0.021	0.300*	0.062	-0.017
	(0.074)	(0.027)	(0.025)	(0.162)	(0.046)	(0.057)
Age	-0.576	0.353**	-0.094	-1.519	0.435	-0.325
	(0.414)	(0.148)	(0.140)	(1.061)	(0.292)	(0.340)
College degree	-0.050	0.032	-0.021	-0.027	-0.024	-0.013
	(0.093)	(0.035)	(0.032)	(0.200)	(0.073)	(0.082)
Observations	2,181	2,181	2,181	591	591	591
Panel B: Wave 4 workday sleep, by 10+ hours/week work status						
Attractive, Wave 1	0.033	-0.040	-0.018	-0.375**	0.039	-0.153**
	(0.064)	(0.028)	(0.023)	(0.167)	(0.057)	(0.062)
Female	0.444***	0.031	0.041	0.468*	0.021	0.122*
	(0.069)	(0.028)	(0.026)	(0.238)	(0.077)	(0.072)
Age	-0.003	-0.368*	-0.143	1.883	-0.555	0.569
	(0.618)	(0.210)	(0.182)	(1.302)	(0.451)	(0.505)
College degree	0.024	-0.072**	-0.016	-0.210	-0.033	-0.075
	(0.074)	(0.030)	(0.025)	(0.202)	(0.065)	(0.084)
Observations	2,066	2,066	2,066	440	440	440

Table 4: College Degree, Wave 1 Attractiveness and Sleep Outcomes by Work Status (continued)

Variable	Work-status group			Comparison group		
	Hours	Short	Long	Hours	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Wave 5 sleep, by work status						
Attractive, Wave 1	0.161***	-0.056**	0.053**	0.021	-0.007	0.087
	(0.052)	(0.027)	(0.023)	(0.194)	(0.081)	(0.094)
Female	0.087*	-0.001	0.084***	0.177	-0.011	0.086
	(0.052)	(0.028)	(0.025)	(0.202)	(0.093)	(0.083)
Age	-0.617	0.446**	-0.196	0.264	0.339	0.258
	(0.386)	(0.211)	(0.183)	(1.315)	(0.622)	(0.655)
College degree	0.161***	-0.113***	0.009	0.187	-0.178**	-0.101
	(0.055)	(0.029)	(0.025)	(0.192)	(0.088)	(0.102)
Observations	2,392	2,392	2,392	295	295	295
Panel D: Wave 6 sleep, by work status						
Attractive, Wave 1	0.142**	-0.087***	0.063**	0.051	-0.037	0.132
	(0.061)	(0.033)	(0.025)	(0.279)	(0.122)	(0.137)
Female	0.270***	-0.062*	0.121***	0.052	-0.087	-0.012
	(0.063)	(0.034)	(0.027)	(0.400)	(0.201)	(0.131)
Age	-0.720	0.250	-0.328	0.352	0.133	-1.551
	(0.746)	(0.365)	(0.350)	(2.887)	(1.289)	(1.260)
College degree	0.174***	-0.086**	0.012	0.290	-0.006	0.269**
	(0.066)	(0.034)	(0.029)	(0.283)	(0.128)	(0.116)
Observations	1,890	1,890	1,890	140	140	140
Control variables	✓	✓	✓	✓	✓	✓
Interviewer fixed effects	✓	✓	✓	✓	✓	✓

Notes: The table reports selected coefficients from weighted single-wave regressions, with standard errors in parentheses. In Panels A, C, and D, Columns 1–3 restrict the sample to workers and Columns 4–6 restrict the sample to non-workers. In Panel B, Wave 4 work status is measured differently: Columns 1–3 restrict to respondents working for pay at least 10 hours per week, and Columns 4–6 restrict to respondents working less than 10 hours per week. Panel A uses Wave 3 workday sleep; Panel B uses Wave 4 workday sleep; Panels C and D use the Wave 5 and Wave 6 adult sleep measures. Control variables include biological sex, US-born status, age, age squared, birth weight, birth weight squared, race and Hispanic-origin indicators, family-formation controls, child controls, and log Wave 1 household income. Family-formation controls are cohabitation and marriage status; child controls use children under age 6 in the Wave 3 household and number of children in Waves 4–6. Standard errors are clustered by interviewer.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: College Degree, Wave 1 Attractiveness and Trouble Falling Asleep, Waves 4 to 6

Variable	Non-age-interacted 5 or more times per week (1)	3 or more times per week (2)	1 or more times per week (3)	Age-interacted 5 or more times per week (4)	3 or more times per week (5)	1 or more times per week (6)
Panel A: Waves 4 to 6 pooled						
Attractive, Wave 1	-0.007	-0.028**	-0.020	-0.032**	-0.089**	-0.023
	(0.006)	(0.010)	(0.011)	(0.012)	(0.030)	(0.066)
Attractive, Wave 1 × Age				0.001*	0.002*	0.000
				(0.000)	(0.001)	(0.002)
Female	0.046***	0.101***	0.078***	0.045***	0.101***	0.078***
	(0.010)	(0.016)	(0.019)	(0.011)	(0.018)	(0.017)
Age	0.022***	0.011	0.021*	0.022***	0.009	0.022*
	(0.005)	(0.008)	(0.010)	(0.005)	(0.008)	(0.010)
College degree	-0.043**	-0.066***	-0.078***	0.001	-0.188***	-0.004
	(0.013)	(0.016)	(0.020)	(0.044)	(0.033)	(0.029)
College degree × Age				-0.001	0.003**	-0.002*
				(0.001)	(0.001)	(0.001)
Observations	8,339	8,339	8,339	8,339	8,339	8,339
Control variables	✓	✓	✓	✓	✓	✓
Wave indicators	✓	✓	✓	✓	✓	✓
Interviewer fixed effects	✓	✓	✓	✓	✓	✓

Notes: The table reports weighted pooled regressions, with standard errors in parentheses. The dependent variables are indicators for trouble falling asleep five or more times per week, three or more times per week, and one or more times per week. All specifications pool Waves 4, 5, and 6. Columns 1–3 report specifications without the interaction between Wave 1 attractiveness and age. Columns 4–6 report specifications that interact Wave 1 attractiveness and college degree with age. Control variables include biological sex, US-born status, age, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, number of children, log Wave 1 household income, and wave indicators. All specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by Wave 1 interviewer, respondent, and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: Lagged Sleep and Attractiveness

Variable	Pooled sample (1)	Male sample (2)	Female sample (3)	Female interaction (4)
Panel A: Waves 2 and 3 pooled				
Lagged sleep hours	0.018 (0.015)	0.017 (0.029)	0.013 (0.020)	0.013 (0.027)
Lagged short sleep	0.034 (0.027)	0.029 (0.046)	0.008 (0.039)	0.040 (0.043)
Lagged long sleep	-0.023 (0.025)	-0.009 (0.048)	-0.044 (0.037)	0.004 (0.044)
Attractive, Wave 1	0.232*** (0.017)	0.229*** (0.026)	0.259*** (0.024)	0.232*** (0.017)
Female	0.091*** (0.018)			0.091 (0.254)
Female × lagged sleep hours				0.003 (0.031)
Female × lagged short sleep				-0.026 (0.056)
Female × lagged long sleep				-0.051 (0.053)
Observations	6,650	3,032	3,415	6,650
Panel B: Wave 4 attractiveness, Wave 3 workday sleep				
Lagged workday sleep hours	-0.011 (0.022)	-0.005 (0.033)	0.009 (0.029)	-0.007 (0.029)
Lagged workday short sleep	-0.041 (0.040)	0.031 (0.061)	-0.054 (0.052)	-0.015 (0.057)
Lagged workday long sleep	-0.021 (0.040)	-0.013 (0.062)	-0.071 (0.057)	-0.033 (0.055)
Attractive, Wave 1	0.174*** (0.021)	0.180*** (0.040)	0.187*** (0.028)	0.173*** (0.021)
Female	0.049** (0.023)			0.097 (0.296)
Female × lagged workday sleep hours				-0.005 (0.038)
Female × lagged workday short sleep				-0.044 (0.077)
Female × lagged workday long sleep				0.018 (0.074)
Observations	3,484	1,467	1,872	3,484
Panel C: Wave 4 attractiveness, Wave 3 work-off average sleep				
Lagged work-off average sleep hours	-0.004 (0.014)	0.029 (0.021)	-0.042** (0.021)	0.024 (0.018)
Lagged work-off average short sleep	0.004 (0.031)	0.080 (0.053)	-0.060 (0.046)	0.049 (0.045)
Lagged work-off average long sleep	-0.004 (0.043)	-0.038 (0.070)	0.052 (0.059)	-0.059 (0.061)
Attractive, Wave 1	0.175*** (0.021)	0.180*** (0.040)	0.190*** (0.028)	0.175*** (0.021)
Female	0.044* (0.023)			0.590*** (0.214)
Female × lagged work-off average sleep hours				-0.065** (0.025)
Female × lagged work-off average short sleep				-0.101* (0.058)
Female × lagged work-off average long sleep				0.118 (0.078)
Observations	3,484	1,467	1,872	3,484

Notes: The table reports weighted regressions; robust standard errors are in parentheses. Panel A uses interviewer-rated attractiveness in Waves 2 and 3 as the dependent variable, with lagged sleep measured in Wave 1 for Wave 2 attractiveness and in Wave 2 for Wave 3 attractiveness. Panels B and C use Wave 4 interviewer-rated attractiveness as the dependent variable and Wave 3 sleep measures as the key regressors. Panels B and C are estimated on the same Wave 4 sample, requiring nonmissing Wave 3 workday and work-off average sleep measures. Column 1 pools males and females, Columns 2 and 3 estimate sex-specific regressions, and Column 4 interacts lagged sleep measures with biological sex. All specifications control for Wave 1 attractiveness and absorb Wave 1 interviewer fixed effects and current-wave interviewer fixed effects. Panel A additionally includes a Wave 3 indicator. Standard errors are clustered by the current-wave interviewer. These specifications are additional reverse-direction checks and are not direct tests of our main life-cycle sleep hypothesis.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

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Online Appendix

Technical Appendix of Conceptual Framework and Table A1–Table A16 are provided in the Online Appendix.

A Online Technical Appendix of the Conceptual Framework

A.1 Dynamic Optimization Problem

This appendix presents the dynamic optimization problem underlying the conceptual framework. An individual allocates time between work, leisure, and sleep over the life cycle. Total available time in period t is normalized to one:

$$1 = h_t + l_t + s_t,$$

where h_t denotes working time, l_t denotes leisure, and s_t denotes sleep duration.

The individual chooses the sequence

$$\{c_t, l_t, s_t, A_{t+1}\}_{t=0}^{T},$$

where c_t denotes consumption and A_{t+1} denotes next-period asset holdings. Working time is determined residually by the time constraint:

$$h_t = 1 - l_t - s_t.$$

Lifetime utility is given by:

$$U = \sum_{t=0}^{T} \beta^t u(c_t, l_t, s_t),$$

subject to the intertemporal budget constraint:

$$A_{t+1} = (1 + r)A_t + w(s_t, \theta_i, t)h_t - c_t,$$

where r is the interest rate and $w(s_t, \theta_i, t)$ denotes the wage rate. The parameter θ_i captures occupational or career type.

Substituting the time constraint into the budget constraint yields:

$$A_{t+1} = (1 + r)A_t + w(s_t, \theta_i, t)(1 - l_t - s_t) - c_t.$$

The dynamic problem can therefore be written using the Lagrangian:

$$\mathcal{L} = \sum_{t=0}^{T} \beta^t \left[u(c_t, l_t, s_t) + \lambda_t \left((1+r)A_t + w(s_t, \theta_i, t)(1 - l_t - s_t) - c_t - A_{t+1} \right) \right].$$

The first-order condition with respect to consumption is:

$$u_c(c_t, l_t, s_t) = \lambda_t.$$

The first-order condition with respect to next-period assets is:

$$\lambda_t = \beta(1+r)\lambda_{t+1}.$$

Combining these two conditions yields the standard Euler equation:

$$u_c(c_t, l_t, s_t) = \beta(1+r)u_c(c_{t+1}, l_{t+1}, s_{t+1}).$$

The first-order condition with respect to sleep is:

$$u_s(c_t, l_t, s_t) + \lambda_t \left[\frac{\partial w}{\partial s_t}(1 - l_t - s_t) - w(s_t, \theta_i, t) \right] = 0.$$

Using $u_c(c_t, l_t, s_t) = \lambda_t$, the condition can be rewritten as:

$$u_s + u_c \left[\frac{\partial w}{\partial s_t} h_t - w(s_t, \theta_i, t) \right] = 0.$$

This condition shows that optimal sleep balances the direct utility value of sleep against its opportunity cost in terms of reduced working time, while incorporating the productivity-enhancing effect of sleep through $\frac{\partial w}{\partial s_t}$.

The main text assumes that

$$\frac{\partial w}{\partial s_t} > 0, \qquad \frac{\partial^2 w}{\partial s_t^2} < 0, \qquad \frac{\partial^2 w}{\partial s_t \partial t} > 0,$$

and

$$\frac{\partial^3 w}{\partial s_t \partial \theta_i \partial t} > 0.$$

These assumptions imply that sleep raises productivity, but at a diminishing rate, that the productivity return to sleep rises with age, and that this age-related increase is stronger in occupations with higher values of θ_i.

The comparative static prediction follows from the interaction between occupational sorting and the age-varying productivity return to sleep. Let a_i denote a source of individual heterogeneity that affects the probability of entering occupations with high values of θ_i. Higher values of a_i increase the likelihood of sorting into occupations in which productivity depends more strongly on cognitive performance, executive functioning, and long-run health maintenance. Formally,

$$\frac{\partial P(\theta_i \text{ high} \mid a_i)}{\partial a_i} > 0.$$

A.2 Comparative Static

This subsection derives the central prediction of the framework: the relationship between occupational type and optimal sleep becomes more positive with age.

Define the sleep first-order condition as

$$F(s_t, \theta_i, t) \equiv u_s(c_t, l_t, s_t) + u_c(c_t, l_t, s_t)\left[w_s(s_t, \theta_i, t)h_t - w(s_t, \theta_i, t)\right] = 0,$$

where $w_s \equiv \partial w / \partial s_t$ and

$$h_t = 1 - l_t - s_t.$$

The term $w_s(s_t, \theta_i, t)h_t$ captures the marginal productivity benefit of sleep, while $w(s_t, \theta_i, t)$ captures the opportunity cost of sleep through reduced working time.

By the implicit function theorem, optimal sleep can be written locally as

$$s_t^* = s^*(\theta_i, t),$$

with

$$\frac{\partial s_t^*}{\partial \theta_i} = -\frac{F_\theta}{F_s}.$$

By the second-order condition, $F_s(s_t, \theta_i, t) < 0$. On the other hand,

$$F_\theta = u_c \left[w_{s\theta}(s_t, \theta_i, t) h_t - w_\theta(s_t, \theta_i, t) \right],$$

where

$$w_{s\theta} = \frac{\partial^2 w}{\partial s_t \partial \theta_i}.$$

The first term measures how occupational type affects the marginal productivity return to sleep, while the second term captures how occupational type affects the wage opportunity cost of sleep. If

$$w_{s\theta}(s_t, \theta_i, t) h_t > w_\theta(s_t, \theta_i, t),$$

then $F_\theta > 0$. Since $F_s < 0$, it follows that

$$\frac{\partial s_t^*}{\partial \theta_i} = -\frac{F_\theta}{F_s} > 0.$$

Thus, individuals employed in occupations with higher values of θ_i optimally choose more sleep because the productivity benefits of sleep are greater in those occupations.

We next examine how this occupational gradient changes with age. Differentiating

$$F_s \frac{\partial s_t^*}{\partial \theta_i} + F_\theta = 0$$

with respect to t yields

$$\left(F_{ss}\frac{\partial s_t^*}{\partial t}+F_{st}\right)\frac{\partial s_t^*}{\partial \theta_i}+F_s\frac{\partial^2 s_t^*}{\partial t\partial \theta_i}+F_{s\theta}\frac{\partial s_t^*}{\partial t}+F_{\theta t}=0.$$

Rearranging gives

$$\frac{\partial^2 s_t^*}{\partial t\partial \theta_i}=-\frac{F_{\theta t}+F_{s\theta}\frac{\partial s_t^*}{\partial t}+F_{st}\frac{\partial s_t^*}{\partial \theta_i}+F_{ss}\frac{\partial s_t^*}{\partial t}\frac{\partial s_t^*}{\partial \theta_i}}{F_s}.$$

Since $F_s<0$, the cross-partial satisfies

$$\frac{\partial^2 s_t^*}{\partial t\partial \theta_i}>0$$

whenever

$$F_{\theta t}+F_{s\theta}\frac{\partial s_t^*}{\partial t}+F_{st}\frac{\partial s_t^*}{\partial \theta_i}+F_{ss}\frac{\partial s_t^*}{\partial t}\frac{\partial s_t^*}{\partial \theta_i}>0.$$

The leading term is $F_{\theta t}$, which captures whether the marginal net benefit of sleep rises more rapidly with age in high-θ_i occupations. It is given by

$$F_{\theta t}=u_c\left[w_{s\theta t}(s_t,\theta_i,t)h_t-w_{\theta t}(s_t,\theta_i,t)\right],$$

where

$$w_{s\theta t}=\frac{\partial^3 w}{\partial s_t\partial \theta_i\partial t}.$$

The maintained assumption

$$\frac{\partial^3 w}{\partial s_t\partial \theta_i\partial t}>0$$

implies that the marginal productivity return to sleep rises more rapidly with age in occupations with higher values of θ_i. For this force to increase optimal sleep, it must dominate any age-related increase in the wage opportunity cost:

$$w_{s\theta t}(s_t,\theta_i,t)h_t>w_{\theta t}(s_t,\theta_i,t).$$

Under this condition,

$$F_{\theta t}>0.$$

The remaining terms capture how the curvature of the first-order condition affects the response of optimal sleep to age and occupational type. A sufficient condition for the central prediction is therefore

$$F_{\theta t} > -\left[F_{s\theta}\frac{\partial s_t^*}{\partial t} + F_{st}\frac{\partial s_t^*}{\partial \theta_i} + F_{ss}\frac{\partial s_t^*}{\partial t}\frac{\partial s_t^*}{\partial \theta_i}\right].$$

That is, the age-related increase in the marginal net benefit of sleep in high-θ_i occupations must be large enough to dominate the curvature terms. When this sufficient condition holds,

$$\frac{\partial^2 s_t^*}{\partial t \partial \theta_i} > 0.$$

This result says that the occupational gradient in sleep becomes more positive with age. Individuals employed in occupations that rely more heavily on cognitive performance, executive functioning, and sustained attention face increasingly strong incentives to preserve sleep as they age.

The empirical prediction follows from occupational sorting. Let a_i denote a source of individual heterogeneity that affects the probability of entering a high-θ_i occupation. Formally,

$$\frac{\partial P(\theta_i \text{ high} \mid a_i)}{\partial a_i} > 0.$$

Combining these conditions yields the prediction that the marginal effect of a_i on sleep duration becomes more positive with age:

$$\frac{\partial^2 s_t^*}{\partial a_i \partial t} > 0.$$

B Online Appendix Tables

Table A1: Summary Statistics by Sex, Wave 2 Lagged Sleep

	Male					Female				
Variable	Obs.	Mean	Std. dev.	Min	Max	Obs.	Mean	Std. dev.	Min	Max
Very attractive, Wave 2	2,156	0.421	0.494	0	1	2,319	0.549	0.498	0	1
Sleep hours, lagged	2,156	7.977	1.090	6	10	2,319	7.866	1.079	6	10
Short sleep, lagged	2,156	0.323	0.468	0	1	2,319	0.340	0.474	0	1
Long sleep, lagged	2,156	0.294	0.456	0	1	2,319	0.246	0.431	0	1
Attractive, Wave 1	2,156	0.422	0.494	0	1	2,319	0.588	0.492	0	1
College degree	2,156	0.000	0.000	0	0	2,319	0.000	0.000	0	0

Table A2: Summary Statistics by Sex, Wave 3 Workday and Off-Day Sleep

	Male					Female				
Variable	Obs.	Mean	Std. dev.	Min	Max	Obs.	Mean	Std. dev.	Min	Max
Workday sleep hours	1,392	7.543	1.287	5	12	1,604	7.968	1.241	5.5	12
Short workday sleep	1,392	0.250	0.433	0	1	1,604	0.288	0.453	0	1
Long workday sleep	1,392	0.252	0.434	0	1	1,604	0.255	0.436	0	1
Off-day sleep hours	1,392	9.044	2.151	6	20	1,604	9.000	1.428	6	14.5
Short off-day sleep	1,392	0.200	0.400	0	1	1,604	0.339	0.474	0	1
Long off-day sleep	1,392	0.302	0.459	0	1	1,604	0.326	0.469	0	1
Sleep hours, lagged	1,048	7.755	1.079	6	10	1,238	7.526	1.161	5	10
Short sleep, lagged	1,048	0.397	0.489	0	1	1,238	0.463	0.499	0	1
Long sleep, lagged	1,048	0.217	0.412	0	1	1,238	0.537	0.499	0	1
High overall task-demand occupation	983	0.139	0.346	0	1	1,081	0.101	0.302	0	1
High cognitive task-demand occupation	983	0.092	0.289	0	1	1,081	0.091	0.287	0	1
High vigilance task-demand occupation	983	0.196	0.397	0	1	1,081	0.061	0.239	0	1
Working	1,392	0.779	0.415	0	1	1,602	0.745	0.436	0	1
Weekly work hours	1,391	31.188	20.119	0	90	1,599	24.944	18.097	0	120
Hangs out socially	1,387	0.492	0.500	0	1	1,602	0.506	0.500	0	1
Attractive, Wave 1	1,392	0.442	0.497	0	1	1,604	0.611	0.488	0	1
Age	1,392	21.895	1.882	18	28	1,604	21.697	1.764	18	27
Birth weight	1,392	3.461	0.558	1.814	5.414	1,604	3.297	0.527	1.814	5.131
Children under age 6 in household	1,392	0.208	0.552	0	4	1,604	0.443	0.769	0	9
Cohabited	1,392	0.122	0.327	0	1	1,604	0.150	0.358	0	1
Married	1,392	0.129	0.336	0	1	1,604	0.206	0.405	0	1
College degree	1,392	0.146	0.353	0	1	1,604	0.179	0.384	0	1
Log household income, Wave 1	1,392	3.287	1.221	0	6.907	1,604	3.271	1.291	0	6.907

Table A3: Summary Statistics by Sex, Wave 4 Workday and Off-Day Sleep

	Male					Female				
Variable	Obs.	Mean	Std. dev.	Min	Max	Obs.	Mean	Std. dev.	Min	Max
Workday sleep hours	1,455	7.395	1.175	5	13	1,790	7.811	1.094	5.083	11
Short workday sleep	1,455	0.262	0.440	0	1	1,790	0.304	0.460	0	1
Long workday sleep	1,455	0.190	0.393	0	1	1,790	0.210	0.407	0	1
Off-day sleep hours	1,455	8.529	1.672	6	18.25	1,790	8.843	1.457	6	19.5
Short off-day sleep	1,455	0.207	0.405	0	1	1,790	0.348	0.477	0	1
Long off-day sleep	1,455	0.225	0.418	0	1	1,790	0.215	0.411	0	1
Trouble falling asleep (0–4)	1,434	1.007	1.210	0	4	1,777	1.208	1.285	0	4
Trouble falling asleep (2+)	1,434	0.318	0.466	0	1	1,777	0.366	0.482	0	1
Trouble falling asleep (3+)	1,434	0.127	0.334	0	1	1,777	0.170	0.376	0	1
Trouble falling asleep (5+ times/week)	1,434	0.054	0.226	0	1	1,777	0.081	0.273	0	1
High overall task-demand occupation	1,419	0.192	0.394	0	1	1,757	0.175	0.380	0	1
High cognitive task-demand occupation	1,419	0.128	0.334	0	1	1,757	0.122	0.328	0	1
High vigilance task-demand occupation	1,419	0.235	0.424	0	1	1,757	0.105	0.306	0	1
Attractive, Wave 1	1,455	0.456	0.498	0	1	1,790	0.603	0.489	0	1
Age	1,455	28.358	1.841	24	33	1,790	28.107	1.784	24	33
Birth weight	1,455	3.455	0.557	1.814	5.188	1,790	3.312	0.532	1.814	5.131
Number of children	1,455	0.726	1.068	0	6	1,790	1.060	1.155	0	7
Cohabited	1,455	0.197	0.398	0	1	1,790	0.179	0.384	0	1
Married	1,455	0.380	0.485	0	1	1,790	0.464	0.499	0	1
College degree	1,455	0.309	0.462	0	1	1,790	0.376	0.484	0	1
Log household income, Wave 1	1,455	3.277	1.267	0	6.907	1,790	3.261	1.294	0	6.907

Table A4: Summary Statistics by Sex, Wave 5

	Male					Female				
Variable	Obs.	Mean	Std. dev.	Min	Max	Obs.	Mean	Std. dev.	Min	Max
Sleep hours	1,233	6.687	0.893	5	8	1,673	6.882	1.000	5	9
Short sleep	1,233	0.429	0.495	0	1	1,673	0.376	0.484	0	1
Long sleep	1,233	0.203	0.402	0	1	1,673	0.300	0.459	0	1
Trouble falling asleep (0–4)	1,233	1.461	1.279	0	4	1,672	1.896	1.311	0	4
Trouble falling asleep (2+)	1,233	0.451	0.498	0	1	1,672	0.595	0.491	0	1
Trouble falling asleep (3+)	1,233	0.218	0.413	0	1	1,672	0.323	0.468	0	1
Trouble falling asleep (5+ times/week)	1,233	0.089	0.285	0	1	1,672	0.155	0.362	0	1
Frequent social gathering	1,231	0.117	0.321	0	1	1,673	0.108	0.310	0	1
High overall task-demand occupation	1,054	0.243	0.429	0	1	1,336	0.183	0.387	0	1
High cognitive task-demand occupation	1,054	0.084	0.278	0	1	1,336	0.062	0.241	0	1
High vigilance task-demand occupation	1,054	0.178	0.383	0	1	1,336	0.068	0.251	0	1
Attractive, Wave 1	1,233	0.428	0.495	0	1	1,673	0.600	0.490	0	1
Age	1,233	36.797	2.065	32	42	1,673	36.346	1.976	32	42
Birth weight	1,233	3.475	0.560	1.814	5.414	1,673	3.316	0.535	1.814	5.131
Number of children	1,233	1.331	1.339	0	6	1,673	1.567	1.297	0	6
Cohabited	1,233	0.154	0.361	0	1	1,673	0.148	0.355	0	1
Married	1,233	0.578	0.494	0	1	1,673	0.593	0.491	0	1
College degree	1,233	0.345	0.476	0	1	1,673	0.449	0.498	0	1
Log household income, Wave 1	1,233	3.318	1.280	0	6.907	1,673	3.258	1.283	0	6.907

Table A5: Summary Statistics by Sex, Wave 6

	Male					Female				
Variable	Obs.	Mean	Std. dev.	Min	Max	Obs.	Mean	Std. dev.	Min	Max
Sleep hours	912	6.631	0.915	5	8	1,333	6.880	0.993	5	9
Short sleep	912	0.427	0.495	0	1	1,333	0.370	0.483	0	1
Long sleep	912	0.180	0.384	0	1	1,333	0.298	0.457	0	1
Trouble falling asleep (0–4)	912	1.784	1.284	0	4	1,332	2.096	1.286	0	4
Trouble falling asleep (2+)	912	0.548	0.498	0	1	1,332	0.659	0.474	0	1
Trouble falling asleep (3+)	912	0.305	0.461	0	1	1,332	0.391	0.488	0	1
Trouble falling asleep (5+ times/week)	912	0.122	0.327	0	1	1,332	0.178	0.383	0	1
Ever diagnosed with depression	912	0.209	0.407	0	1	1,333	0.310	0.463	0	1
Ever diagnosed with anxiety	912	0.113	0.317	0	1	1,333	0.246	0.431	0	1
Ever diagnosed with panic attacks	912	0.071	0.257	0	1	1,333	0.129	0.336	0	1
Current depression	912	0.145	0.353	0	1	1,331	0.212	0.409	0	1
Current anxiety	912	0.091	0.288	0	1	1,333	0.203	0.402	0	1
Current panic attacks	912	0.039	0.194	0	1	1,333	0.095	0.293	0	1
Working	912	0.900	0.300	0	1	1,331	0.845	0.362	0	1
Weekly work hours	910	40.847	17.412	0	120	1,329	34.367	18.326	0	120
Frequent social gathering	911	0.097	0.296	0	1	1,332	0.094	0.292	0	1
High overall task-demand occupation	786	0.286	0.452	0	1	1,115	0.206	0.404	0	1
High cognitive task-demand occupation	786	0.114	0.318	0	1	1,115	0.083	0.276	0	1
High vigilance task-demand occupation	786	0.172	0.377	0	1	1,115	0.074	0.262	0	1
Attractive, Wave 1	912	0.456	0.498	0	1	1,333	0.600	0.490	0	1
Age	912	44.213	1.964	40	49	1,333	43.914	1.859	40	49
Birth weight	912	3.477	0.561	1.814	5.188	1,333	3.307	0.522	1.814	4.990
Number of children	912	1.672	1.611	0	11	1,333	1.792	1.440	0	10
Cohabited	912	0.086	0.280	0	1	1,333	0.093	0.290	0	1
Married	912	0.585	0.493	0	1	1,333	0.600	0.490	0	1
College degree	912	0.398	0.490	0	1	1,333	0.492	0.500	0	1
Log household income, Wave 1	912	3.392	1.209	0	6.907	1,333	3.296	1.316	0	6.907

Table A6: High Task-Demand Occupations by Wave

Variable	Overall (1)	Cognitive (2)	Vigilance (3)
Panel A: Wave 3			
Attractive, Wave 1	0.039**	0.021	0.016
	(0.019)	(0.017)	(0.018)
Female	-0.047**	-0.001	-0.133***
	(0.019)	(0.020)	(0.021)
College degree	0.090***	0.085***	-0.029
	(0.031)	(0.029)	(0.030)
Observations	1,972	1,972	1,972
Panel B: Wave 4			
Attractive, Wave 1	0.029	0.032*	0.018
	(0.020)	(0.016)	(0.017)
Female	-0.021	-0.008	-0.138***
	(0.017)	(0.015)	(0.020)
College degree	0.150***	0.156***	0.013
	(0.021)	(0.018)	(0.018)
Observations	3,112	3,112	3,112
Panel C: Wave 5			
Attractive, Wave 1	0.055**	-0.005	-0.014
	(0.023)	(0.015)	(0.018)
Female	-0.066***	-0.043***	-0.126***
	(0.023)	(0.016)	(0.020)
College degree	0.118***	0.077***	-0.045***
	(0.024)	(0.015)	(0.017)
Observations	2,318	2,318	2,318
Panel D: Wave 6			
Attractive, Wave 1	0.062**	0.035*	0.053**
	(0.028)	(0.020)	(0.023)
Female	-0.065**	-0.013	-0.085***
	(0.028)	(0.019)	(0.025)
College degree	0.120***	0.061***	-0.078***
	(0.027)	(0.022)	(0.023)
Observations	1,816	1,816	1,816
Control variables	✓	✓	✓
Interviewer fixed effects	✓	✓	✓

Notes: The table reports weighted wave-specific regressions, with standard errors in parentheses. The dependent variables are indicators for whether the respondent's occupation is in the top quartile of the corresponding task-demand index. Reported covariates are Wave 1 attractiveness, female, and college degree. Additional controls include US-born status, age, age squared, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, log Wave 1 household income, and the wave indicator; child controls are included where available. All specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by Wave 1 interviewer.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A7a: Robustness Checks for Pooled Workday Sleep-Duration Estimates

Variable	Sleep hours	Short sleep	Long sleep
	(1)	(2)	(3)
Panel A: Waves 4 to 6 pooled, work-off average in Wave 4			
Attractive, Wave 1	-0.454***	0.170***	-0.273***
	(0.050)	(0.023)	(0.022)
Attractive, Wave 1 × Age	0.014***	-0.006***	0.008***
	(0.002)	(0.001)	(0.001)
College degree	-0.498***	0.024	-0.240***
	(0.082)	(0.048)	(0.027)
College degree × Age	0.016***	-0.003*	0.006***
	(0.003)	(0.002)	(0.001)
Female	0.292***	0.000	0.047
	(0.046)	(0.023)	(0.032)
Age	-0.031***	0.010**	-0.008*
	(0.008)	(0.003)	(0.004)
Observations	8,348	8,348	8,348
Panel B: Waves 2 to 6 pooled, workday-style measure, no child controls			
Attractive, Wave 1	-0.247***	0.080***	-0.074
	(0.039)	(0.019)	(0.043)
Attractive, Wave 1 × Age	0.009***	-0.004***	0.002
	(0.001)	(0.001)	(0.002)
College degree	-0.480***	0.060	-0.221***
	(0.092)	(0.040)	(0.034)
College degree × Age	0.017***	-0.004***	0.006***
	(0.003)	(0.001)	(0.001)
Female	0.172	0.018	0.128**
	(0.147)	(0.022)	(0.057)
Age	-0.061**	0.018*	-0.018**
	(0.022)	(0.009)	(0.007)
Observations	14,960	14,960	14,960
Control variables	✓	✓	✓
Wave indicators	✓	✓	✓
Interviewer fixed effects	✓	✓	✓

Notes: The table reports weighted pooled sleep regressions, with standard errors in parentheses. Only the age-interaction specifications are shown. Panel A pools Waves 4 to 6 and uses the work-off average sleep-hours measure in Wave 4. Panel B pools Waves 2 to 6 using the workday-style sleep measure and omits child controls. The specifications interact Wave 1 attractiveness and college degree with age. Controls include biological sex, US-born status, age, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, college degree where not absorbed by the interaction parameterization, log Wave 1 household income, and wave indicators; Panel A also includes number of children. Specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by respondent, Wave 1 interviewer, and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A7b: Female-Interacted Pooled Workday Sleep-Duration Robustness Checks **(continued on next page)**

Variable	Sleep hours (1)	Short sleep (2)	Long sleep (3)
Panel C: Waves 4 to 6 pooled, workday measure			
Attractive, Wave 1	-0.687***	0.177**	-0.253***
	(0.089)	(0.056)	(0.038)
Attractive, Wave 1 × Age	0.020***	-0.006***	0.007***
	(0.003)	(0.002)	(0.001)
Female × Attractive, Wave 1 × Age	-0.013***	0.002	-0.002
	(0.003)	(0.002)	(0.002)
College degree	-0.531***	0.058	-0.197***
	(0.084)	(0.052)	(0.026)
College degree × Age	0.016***	-0.003	0.005***
	(0.003)	(0.002)	(0.001)
Female × College degree × Age	0.001	-0.001	0.000
	(0.003)	(0.001)	(0.001)
Female	0.547***	0.082	-0.141**
	(0.090)	(0.057)	(0.046)
Age	-0.025***	0.010**	-0.011***
	(0.007)	(0.003)	(0.003)
Observations	8,375	8,375	8,375

Table A7b: Female-Interacted Pooled Workday Sleep-Duration Robustness Checks (continued)

Variable	Sleep hours (1)	Short sleep (2)	Long sleep (3)
Panel D: Waves 3 to 6 pooled, workday measure, no child controls			
Attractive, Wave 1	-0.299*	0.067	-0.115*
	(0.138)	(0.046)	(0.053)
Attractive, Wave 1 × Age	0.009**	-0.003*	0.003**
	(0.004)	(0.002)	(0.002)
Female × Attractive, Wave 1 × Age	0.002	-0.000	0.003
	(0.006)	(0.001)	(0.002)
College degree	-0.520***	0.067*	-0.196***
	(0.080)	(0.032)	(0.030)
College degree × Age	0.017***	-0.004**	0.005***
	(0.003)	(0.001)	(0.001)
Female × College degree × Age	0.001	-0.000	0.000
	(0.002)	(0.001)	(0.001)
Female	0.701***	0.048	0.076
	(0.100)	(0.042)	(0.078)
Age	-0.030***	0.009***	-0.011***
	(0.005)	(0.003)	(0.002)
Observations	11,380	11,380	11,380
Control variables	✓	✓	✓
Wave indicators	✓	✓	✓
Interviewer fixed effects	✓	✓	✓

Notes: The table reports weighted pooled workday sleep regressions, with standard errors in parentheses. Panels C and D allow the attractiveness-age gradient and the college-age gradient to differ by biological sex. Panel C pools Waves 4 to 6 and includes number of children. Panel D pools Waves 3 to 6 and omits child controls. Controls include US-born status, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, log Wave 1 household income, and wave indicators. Specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by respondent, Wave 1 interviewer, and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A8: Alternative Wave 1 Attractiveness Measures in Pooled Workday Sleep-Duration Estimates

Variable	Sleep hours	Short sleep	Long sleep
	(1)	(2)	(3)
Panel A: Waves 4 to 6 pooled, workday measure			
Very attractive, Wave 1	-0.581***	0.256***	-0.309***
	(0.084)	(0.050)	(0.043)
Very attractive, Wave 1 × Age	0.019***	-0.009***	0.009***
	(0.002)	(0.002)	(0.001)
Attractive, Wave 1	-0.236***	0.112***	-0.186***
	(0.068)	(0.027)	(0.042)
Attractive, Wave 1 × Age	0.008***	-0.004***	0.006***
	(0.002)	(0.001)	(0.001)
College degree	-0.498***	0.061	-0.210***
	(0.088)	(0.050)	(0.022)
College degree × Age	0.016***	-0.004**	0.006***
	(0.003)	(0.002)	(0.001)
Female	0.320***	-0.021	0.065**
	(0.067)	(0.016)	(0.021)
Age	-0.029***	0.009**	-0.009**
	(0.008)	(0.003)	(0.003)
Observations	8,375	8,375	8,375
Panel B: Waves 3 to 6 pooled, workday measure, no child controls			
Very attractive, Wave 1	-0.350***	0.143**	-0.208***
	(0.093)	(0.056)	(0.048)
Very attractive, Wave 1 × Age	0.012***	-0.006***	0.006***
	(0.003)	(0.002)	(0.002)
Attractive, Wave 1	-0.215***	0.057*	-0.141***
	(0.047)	(0.032)	(0.032)
Attractive, Wave 1 × Age	0.007***	-0.003**	0.004***
	(0.002)	(0.001)	(0.001)
College degree	-0.495***	0.069**	-0.195***
	(0.081)	(0.030)	(0.028)
College degree × Age	0.016***	-0.004***	0.005***
	(0.003)	(0.001)	(0.001)
Female	0.336***	-0.008	0.063***
	(0.042)	(0.011)	(0.014)
Age	-0.036***	0.008***	-0.011***
	(0.006)	(0.002)	(0.002)
Observations	11,380	11,380	11,380
Control variables	✓	✓	✓
Wave indicators	✓	✓	✓
Interviewer fixed effects	✓	✓	✓

Notes: The table reports weighted pooled workday sleep regressions, with standard errors in parentheses. Only the age-interaction specifications are shown. The main Wave 1 attractiveness indicator is replaced by separate indicators for respondents rated very attractive and attractive at Wave 1, each interacted with age. Panel A pools Waves 4 to 6 and includes number of children. Panel B pools Waves 3 to 6 and omits child controls. All columns include the college-age interaction. Controls include biological sex, US-born status, age, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, college degree, log Wave 1 household income, and wave indicators; Panel A also includes number of children. Specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by respondent, Wave 1 interviewer, and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A9: Pooled Workday Sleep-Duration Robustness Checks with Additional Wave 1 Controls (continued on next page)

	Non-age-interacted			Age-interacted		
Variable	Hours	Short	Long	Hours	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Waves 4 to 6 pooled, workday measure						
Attractive, Wave 1	0.054	-0.037	0.007	-0.364***	0.165***	-0.225***
	(0.050)	(0.021)	(0.025)	(0.069)	(0.030)	(0.035)
Attractive, Wave 1 × Age				0.012***	-0.006***	0.007***
				(0.002)	(0.001)	(0.001)
College degree	0.055	-0.058**	-0.007	-0.502***	0.074	-0.212***
	(0.079)	(0.020)	(0.026)	(0.075)	(0.045)	(0.025)
College degree × Age				0.016***	-0.004**	0.006***
				(0.002)	(0.001)	(0.001)
Female	0.335***	-0.028	0.069**	0.338***	-0.029	0.070**
	(0.065)	(0.017)	(0.023)	(0.065)	(0.017)	(0.023)
Age	-0.040*	-0.003	-0.011	-0.031***	0.010***	-0.010**
	(0.020)	(0.011)	(0.007)	(0.008)	(0.003)	(0.003)
Observations	8,265	8,265	8,265	8,265	8,265	8,265

Table A9: Pooled Workday Sleep-Duration Robustness Checks with Additional Wave 1 Controls (continued)

Variable	Non-age-interacted			Age-interacted		
	Hours	Short	Long	Hours	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Waves 3 to 6 pooled, workday measure, no child controls						
Attractive, Wave 1	0.009	-0.028*	-0.012	-0.261***	0.092**	-0.162***
	(0.040)	(0.013)	(0.017)	(0.056)	(0.035)	(0.032)
Attractive, Wave 1 × Age				0.009***	-0.004***	0.005***
				(0.002)	(0.001)	(0.001)
College degree	0.043	-0.056***	-0.013	-0.506***	0.075**	-0.203***
	(0.069)	(0.017)	(0.022)	(0.076)	(0.028)	(0.030)
College degree × Age				0.017***	-0.004***	0.006***
				(0.002)	(0.001)	(0.001)
Female	0.346***	-0.013	0.064***	0.351***	-0.014	0.066***
	(0.043)	(0.011)	(0.015)	(0.042)	(0.012)	(0.015)
Age	-0.086***	0.001	-0.029**	-0.038***	0.008***	-0.012***
	(0.022)	(0.007)	(0.010)	(0.006)	(0.002)	(0.002)
Observations	11,229	11,229	11,229	11,229	11,229	11,229
Control variables	✓	✓	✓	✓	✓	✓
Additional Wave 1 controls	✓	✓	✓	✓	✓	✓
Wave indicators	✓	✓	✓	✓	✓	✓
Interviewer fixed effects	✓	✓	✓	✓	✓	✓

Notes: The table reports weighted pooled workday sleep regressions, with standard errors in parentheses. Panel A pools Waves 4 to 6 and includes number of children. Panel B pools Waves 3 to 6 and omits child controls. Columns 1–3 report non-age-interacted specifications; columns 4–6 report specifications that interact Wave 1 attractiveness and college degree with age. Additional Wave 1 controls include indicators for neighborhood upkeep, area type, residence type, neighborhood safety, self-pride, good qualities, social acceptance, and health. Other controls include biological sex, US-born status, age, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, college degree where not absorbed by the interaction parameterization, log Wave 1 household income, and wave indicators. Specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by respondent, Wave 1 interviewer, and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A10: Balanced-Panel Robustness Checks for Pooled Workday Sleep-Duration Age-Interaction Estimates

Variable	Sleep hours	Short sleep	Long sleep
	(1)	(2)	(3)
Panel A: Waves 4 to 6 pooled, balanced Table 3 sample			
Attractive, Wave 1	-0.081	0.112**	-0.135***
	(0.085)	(0.037)	(0.028)
Attractive, Wave 1 × Age	0.004	-0.003***	0.004***
	(0.002)	(0.001)	(0.001)
College degree	-0.303**	0.035	-0.205***
	(0.095)	(0.053)	(0.012)
College degree × Age	0.010***	-0.002	0.006***
	(0.003)	(0.001)	(0.001)
Female	0.377***	-0.055***	0.081***
	(0.090)	(0.014)	(0.019)
Age	-0.015*	0.005	-0.006
	(0.008)	(0.003)	(0.003)
Observations	5,079	5,079	5,079
Panel B: Waves 3 to 6 pooled, balanced Table 3 sample			
Attractive, Wave 1	-0.010	0.002	-0.110***
	(0.042)	(0.034)	(0.022)
Attractive, Wave 1 × Age	0.002*	-0.001	0.003***
	(0.001)	(0.001)	(0.001)
College degree	-0.582***	0.076	-0.251***
	(0.123)	(0.043)	(0.036)
College degree × Age	0.017***	-0.004***	0.007***
	(0.003)	(0.001)	(0.001)
Female	0.317***	-0.013	0.066***
	(0.067)	(0.017)	(0.017)
Age	-0.027**	0.004	-0.011***
	(0.010)	(0.003)	(0.003)
Observations	4,732	4,732	4,732
Control variables	✓	✓	✓
Wave indicators	✓	✓	✓
Interviewer fixed effects	✓	✓	✓

Notes: The table reports weighted pooled workday sleep regressions, with standard errors in parentheses. Only the age-interaction specifications are shown. Panel A pools Waves 4 to 6, includes number of children, and restricts the sample to respondents observed with complete Table 3 variables in Waves 4, 5, and 6. Panel B pools Waves 3 to 6, omits child controls, and restricts the sample to respondents observed with complete Table 3 variables in Waves 3, 4, 5, and 6. Controls include biological sex, US-born status, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, log Wave 1 household income, and wave indicators. Specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by respondent, Wave 1 interviewer, and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A11: Inverse-Probability-Weighted Attrition Robustness Checks for Pooled Workday Sleep-Duration Age-Interaction Estimates

Variable	Sleep hours (1)	Short sleep (2)	Long sleep (3)
Panel A: Waves 4 to 6 pooled, IPW attrition correction			
Attractive, Wave 1	-0.433***	0.191***	-0.246***
	(0.072)	(0.037)	(0.035)
Attractive, Wave 1 × Age	0.013***	-0.006***	0.007***
	(0.002)	(0.001)	(0.001)
College degree	-0.496***	0.037	-0.197***
	(0.107)	(0.055)	(0.018)
College degree × Age	0.015***	-0.003*	0.005***
	(0.003)	(0.001)	(0.000)
Age	-0.029***	0.011***	-0.009**
	(0.007)	(0.003)	(0.003)
Observations	8,274	8,274	8,274
Panel B: Waves 3 to 6 pooled, IPW attrition correction			
Attractive, Wave 1	-0.295***	0.114***	-0.168***
	(0.054)	(0.030)	(0.031)
Attractive, Wave 1 × Age	0.010***	-0.004***	0.005***
	(0.002)	(0.001)	(0.001)
College degree	-0.502***	0.049**	-0.196***
	(0.059)	(0.019)	(0.023)
College degree × Age	0.015***	-0.003***	0.005***
	(0.002)	(0.001)	(0.001)
Age	-0.033***	0.009***	-0.011***
	(0.004)	(0.003)	(0.002)
Observations	11,224	11,224	11,224
Control variables	✓	✓	✓
Wave indicators	✓	✓	✓
Interviewer fixed effects			

Notes: The table reports inverse-probability-weighted pooled workday sleep regressions, with standard errors in parentheses. Only the age-interaction specifications are shown. Panel A pools Waves 4 to 6 and includes number of children. Panel B pools Waves 3 to 6 and omits child controls. The attrition weights divide the public-use pooled analysis weight by the predicted probability of being observed in the relevant wave-specific Table 3 analysis sample. Predicted probabilities are estimated using Wave 1 attractiveness, biological sex, age, U.S.-born status, birth weight, birth weight squared, race and Hispanic-origin indicators, Wave 1 household income, Wave 1 sleep, and additional Wave 1 neighborhood, residence, psychosocial, and health controls. Outcome regressions include biological sex, U.S.-born status, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, log Wave 1 household income, and wave indicators. Standard errors are clustered by respondent and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A12: Pooled Workday Sleep-Duration Estimates with Wave 1 Sleep Controls **(continued on next page)**

	Non-age-interacted			Age-interacted		
Variable	Hours	Short	Long	Hours	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Waves 4 to 6 pooled, workday measure						
Attractive, Wave 1	0.053	-0.032	0.013	-0.334***	0.183***	-0.211***
	(0.049)	(0.023)	(0.025)	(0.065)	(0.038)	(0.030)
Attractive, Wave 1 × Age				0.011***	-0.006***	0.006***
				(0.002)	(0.001)	(0.001)
College degree	0.040	-0.063**	-0.018	-0.462***	0.047	-0.197***
	(0.092)	(0.023)	(0.026)	(0.114)	(0.060)	(0.016)
College degree × Age				0.014***	-0.003*	0.005***
				(0.003)	(0.002)	(0.000)
Age	-0.019*	-0.018***	-0.013**	-0.007	0.002	-0.005
	(0.009)	(0.005)	(0.005)	(0.007)	(0.004)	(0.003)
Sleep hours, Wave 1	0.095***	-0.022*	0.015	0.092***	-0.021*	0.014
	(0.026)	(0.011)	(0.010)	(0.026)	(0.011)	(0.010)
Short sleep, Wave 1	-0.006	0.010	-0.018	-0.010	0.010	-0.019
	(0.046)	(0.023)	(0.015)	(0.047)	(0.024)	(0.015)
Long sleep, Wave 1	-0.061	0.011	-0.007	-0.054	0.008	-0.003
	(0.059)	(0.020)	(0.018)	(0.056)	(0.020)	(0.018)
Observations	7,925	7,925	7,925	7,925	7,925	7,925

Table A12: Pooled Workday Sleep-Duration Estimates with Wave 1 Sleep Controls (continued)

	Non-age-interacted			Age-interacted		
Variable	Hours	Short	Long	Hours	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Waves 3 to 6 pooled, workday measure, no child controls						
Attractive, Wave 1	0.014	-0.020	-0.003	-0.247***	0.108***	-0.143***
	(0.037)	(0.015)	(0.016)	(0.042)	(0.034)	(0.028)
Attractive, Wave 1 × Age				0.009***	-0.004***	0.005***
				(0.001)	(0.001)	(0.001)
College degree	0.017	-0.058***	-0.025	-0.486***	0.060*	-0.197***
	(0.065)	(0.016)	(0.022)	(0.086)	(0.030)	(0.029)
College degree × Age				0.015***	-0.004***	0.005***
				(0.002)	(0.001)	(0.001)
Age	-0.075***	-0.003	-0.027***	-0.016**	0.003	-0.008***
	(0.019)	(0.007)	(0.006)	(0.006)	(0.003)	(0.002)
Sleep hours, Wave 1	0.075**	-0.019**	0.017*	0.073**	-0.019**	0.016*
	(0.027)	(0.008)	(0.009)	(0.027)	(0.008)	(0.009)
Short sleep, Wave 1	-0.054	0.015	-0.016	-0.055	0.015	-0.016
	(0.046)	(0.018)	(0.016)	(0.047)	(0.018)	(0.015)
Long sleep, Wave 1	-0.057	0.017	-0.018	-0.052	0.015	-0.015
	(0.049)	(0.016)	(0.015)	(0.049)	(0.016)	(0.015)
Observations	10,730	10,730	10,730	10,730	10,730	10,730
Control variables	✓	✓	✓	✓	✓	✓
Wave indicators	✓	✓	✓	✓	✓	✓
Wave 1 sleep controls	✓	✓	✓	✓	✓	✓

Notes: The table reports weighted pooled workday sleep regressions, with standard errors in parentheses. Panel A pools Waves 4 to 6 and includes number of children. Panel B pools Waves 3 to 6 and omits child controls. Columns 1–3 report non-age-interacted specifications; columns 4–6 report specifications that interact Wave 1 attractiveness and college degree with age. Relative to Table 3, all specifications add Wave 1 sleep hours, Wave 1 short sleep, and Wave 1 long sleep as controls. Other controls include biological sex, US-born status, age, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, college degree where not absorbed by the interaction parameterization, log Wave 1 household income, and wave indicators. Standard errors are clustered by respondent and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A13: Sleep Outcomes by Wave and High Overall Task-Demand Occupations

Variable	Sleep hours (1)	Short sleep (2)	Long sleep (3)
Panel A: Wave 3 workday			
High overall task-demand occupation	-0.221***	0.048	-0.059**
	(0.084)	(0.031)	(0.028)
Female	0.420***	0.016	-0.011
	(0.056)	(0.020)	(0.019)
Observations	2,064	2,064	2,064
Panel B: Wave 4 workday			
High overall task-demand occupation	-0.157***	0.026	-0.045**
	(0.052)	(0.021)	(0.019)
Female	0.411***	0.046***	0.022
	(0.041)	(0.016)	(0.015)
Observations	3,176	3,176	3,176
Panel C: Wave 5			
High overall task-demand occupation	0.067	-0.052**	0.003
	(0.046)	(0.024)	(0.021)
Female	0.169***	-0.051**	0.099***
	(0.038)	(0.020)	(0.017)
Observations	2,390	2,390	2,390
Panel D: Wave 6			
High overall task-demand occupation	0.027	-0.055**	-0.033
	(0.050)	(0.026)	(0.023)
Female	0.258***	-0.082***	0.118***
	(0.043)	(0.023)	(0.020)
Observations	1,901	1,901	1,901
Control variables	✓	✓	✓

Notes: The table reports selected coefficient estimates from weighted wave-specific regressions, with standard errors in parentheses. The Wave 3 and Wave 4 panels use workday sleep measures; Waves 5 and 6 use the available adult sleep measures. The key regressor is an indicator for whether the respondent's occupation is in the top quartile of the overall task-demand index. Control variables include biological sex, US-born status, age, age squared, birth weight, birth weight squared, race and Hispanic-origin indicators, family-formation controls, and log Wave 1 household income. Family-formation controls are cohabitation and marriage status; child controls are included where available.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A14: College Degree, Wave 1 Attractiveness and Wave 6 Mental Health Outcomes

	Main specification			Female-interaction specification		
Variable	Depression	Anxiety	Panic attack	Depression	Anxiety	Panic attack
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Ever diagnosed						
Attractive, Wave 1	-0.034	-0.005	-0.001	-0.035	-0.007	-0.010
	(0.026)	(0.022)	(0.020)	(0.036)	(0.029)	(0.026)
Female	0.114***	0.132***	0.074***	0.153***	0.166***	0.074***
	(0.026)	(0.023)	(0.017)	(0.042)	(0.037)	(0.028)
Female × Attractive, Wave 1				-0.003	0.000	0.015
				(0.048)	(0.044)	(0.035)
College degree	-0.049**	-0.029	-0.023	0.002	0.019	-0.013
	(0.025)	(0.023)	(0.020)	(0.038)	(0.033)	(0.026)
Female × College degree				-0.089*	-0.083*	-0.017
				(0.053)	(0.045)	(0.037)
Observations	2,163	2,163	2,163	2,163	2,163	2,163
Panel B: Current condition						
Attractive, Wave 1	-0.028	0.000	-0.004	-0.021	0.000	-0.022
	(0.022)	(0.020)	(0.017)	(0.030)	(0.026)	(0.019)
Female	0.092***	0.110***	0.061***	0.136***	0.130***	0.058**
	(0.024)	(0.021)	(0.014)	(0.039)	(0.035)	(0.025)
Female × Attractive, Wave 1				-0.016	-0.002	0.031
				(0.042)	(0.038)	(0.029)
College degree	-0.077***	-0.033	-0.035**	-0.029	-0.006	-0.015
	(0.020)	(0.021)	(0.016)	(0.031)	(0.028)	(0.017)
Female × College degree				-0.085*	-0.046	-0.033
				(0.045)	(0.041)	(0.031)
Observations	2,161	2,163	2,163	2,161	2,163	2,163
Control variables	✓	✓	✓	✓	✓	✓
Interviewer fixed effects	✓	✓	✓	✓	✓	✓

Notes: The table reports weighted Wave 6 regression coefficients, with standard errors in parentheses. Panel A uses lifetime diagnosis indicators as dependent variables; Panel B uses current-condition indicators. Columns 4–6 interact biological sex with Wave 1 attractiveness and college degree; in those columns, the main coefficients report the estimates for males, and the interaction rows report the additional coefficients for females. Control variables include biological sex and college degree where not absorbed by the interaction parameterization, US-born status, age, age squared, birth weight, birth weight squared, race and Hispanic-origin indicators, log Wave 1 household income, and the Wave 6 indicator. All specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by Wave 1 interviewer.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A15: College Degree, Wave 1 Attractiveness, Age, and Trouble Falling Asleep with Female Interactions

Variable	5 or more times per week (1)	3 or more times per week (2)	1 or more times per week (3)
Waves 4 to 6 pooled			
Attractive, Wave 1	-0.069**	-0.201***	-0.009
	(0.022)	(0.044)	(0.045)
Female	-0.132***	-0.147**	-0.090
	(0.018)	(0.050)	(0.061)
Age	0.017**	0.002	0.016
	(0.005)	(0.009)	(0.010)
Female × Attractive, Wave 1	0.094**	0.248***	0.000
	(0.034)	(0.054)	(0.036)
Attractive, Wave 1 × Age	0.002**	0.004**	-0.000
	(0.001)	(0.001)	(0.002)
Female × Attractive, Wave 1 × Age	-0.003**	-0.006***	-0.000
	(0.001)	(0.002)	(0.001)
College degree	-0.062	-0.145	-0.098
	(0.053)	(0.087)	(0.071)
College degree × Age	0.001	0.003	0.002
	(0.002)	(0.003)	(0.002)
Female × College degree × Age	-0.005**	-0.001	-0.007*
	(0.002)	(0.004)	(0.003)
Observations	8,339	8,339	8,339
Control variables	✓	✓	✓
Wave indicators	✓	✓	✓
Interviewer fixed effects	✓	✓	✓

Notes: The table reports weighted pooled regressions, with standard errors in parentheses. The dependent variables are indicators for trouble falling asleep five or more times per week, three or more times per week, and one or more times per week. All specifications pool Waves 4, 5, and 6 and interact biological sex, Wave 1 attractiveness, and age. The coefficient on Wave 1 attractiveness is the estimate for males, and the female-interaction rows report additional coefficients for females. Control variables include US-born status, age squared, birth weight, birth weight squared, race and Hispanic-origin indicators, cohabitation, marriage, number of children, college terms shown in the table, log Wave 1 household income, and wave indicators. All specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by Wave 1 interviewer, respondent, and interview year.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A16: College Degree, Wave 1 Attractiveness and Social Gathering by Wave

Variable	Main specification (1)	Female interaction (2)
Panel A: Wave 3		
Attractive, Wave 1	-0.019	-0.037
	(0.024)	(0.033)
Female	0.033	0.013
	(0.023)	(0.035)
Female × Attractive, Wave 1		0.036
		(0.044)
College degree	0.033	0.034
	(0.032)	(0.032)
Observations	2,934	2,934
Panel B: Wave 5		
Attractive, Wave 1	0.001	-0.005
	(0.017)	(0.024)
Female	0.021	0.015
	(0.017)	(0.024)
Female × Attractive, Wave 1		0.012
		(0.031)
College degree	-0.000	0.000
	(0.017)	(0.017)
Observations	2,826	2,826
Panel C: Wave 6		
Attractive, Wave 1	-0.006	-0.006
	(0.018)	(0.027)
Female	0.022	0.022
	(0.018)	(0.025)
Female × Attractive, Wave 1		0.000
		(0.035)
College degree	-0.016	-0.016
	(0.017)	(0.017)
Observations	2,161	2,161
Control variables	✓	✓
Interviewer fixed effects	✓	✓

Notes: The table reports weighted regressions, with standard errors in parentheses. Panel A uses the Wave 3 hang-out measure as the dependent variable. Panels B and C use the frequency of social gathering as the dependent variable. Columns 2 interact biological sex with Wave 1 attractiveness; in those columns, the coefficient on attractiveness is the estimate for males, and the interaction row reports the additional coefficient for females. Control variables include biological sex where not absorbed by the interaction parameterization, US-born status, age, age squared, birth weight, birth weight squared, race and Hispanic-origin indicators, family-formation controls, child controls, college degree, log Wave 1 household income, and the wave indicator. Family-formation controls are cohabitation and marriage status. Child controls are children under age 6 in Wave 3 and number of children in Waves 5 and 6. All specifications absorb Wave 1 interviewer fixed effects. Standard errors are clustered by Wave 1 interviewer.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$